Machine Learning-Based Gas Fields Management: Water and Sand Analytics

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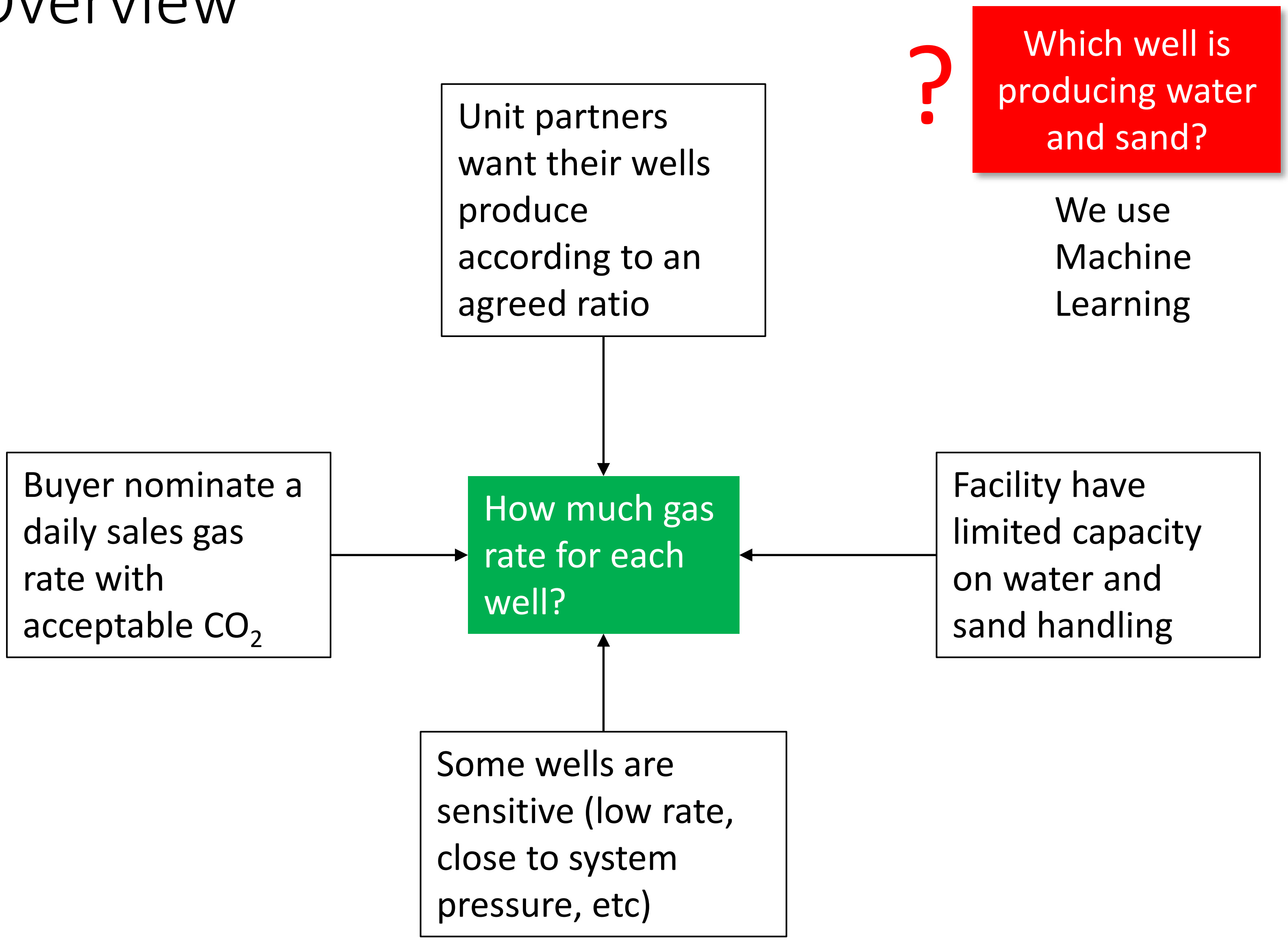
Overview

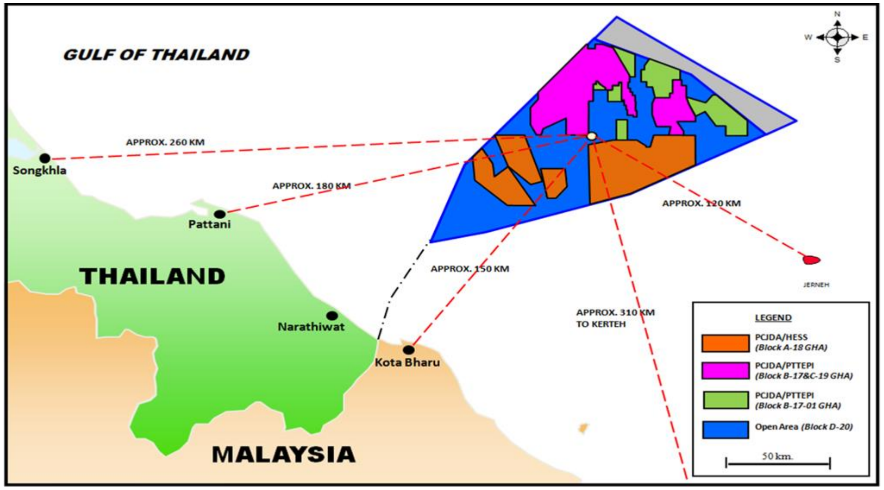

?
Which well is producing water and sand?
We use Machine Learning
Unit partners want their wells produce according to an agreed ratio
Buyer nominate a daily sales gas rate with acceptable CO_2
How much gas rate for each well?
Facility have limited capacity on water and sand handling
Some wells are sensitive (low rate, close to system pressure, etc)

Outline

- A brief overview of our operations
- The objectives of our operations
- Formulating the objectives as an optimization problem
- Major constraints:
  - Well water rate
  - Well sand rate
- Identifying water producing wells
- Identifying sand producing wells

A Brief Overview of Our Operations (1)

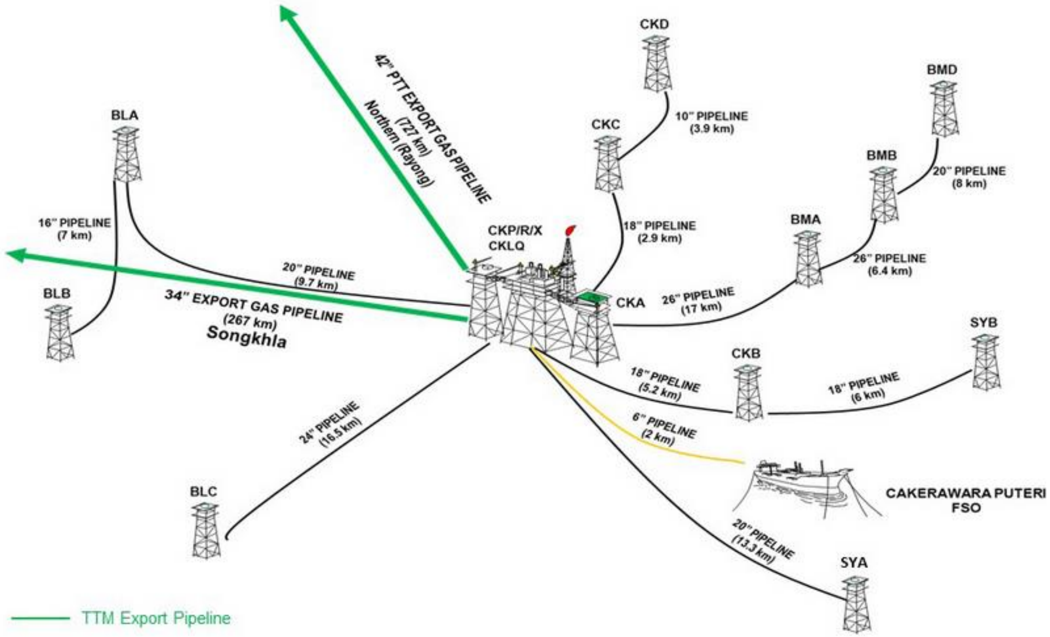
- Complex Geology:
  - Multiple stacked tidal to shallow marine sands
  - Facies ranging from:
    - Low quality bioturbated sand
    - Intermediate quality heterolithic sands
    - High quality massive channel sand



Source: mtja.org

A Brief Overview of Our Operations (2)

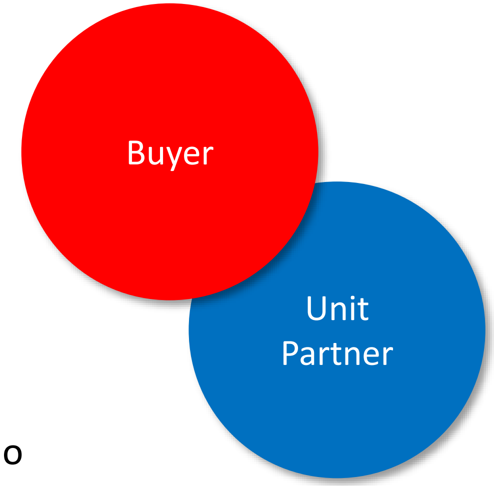
- 12 wellhead platforms
- Numerous development wells
- Single processing hub
- Limited metering

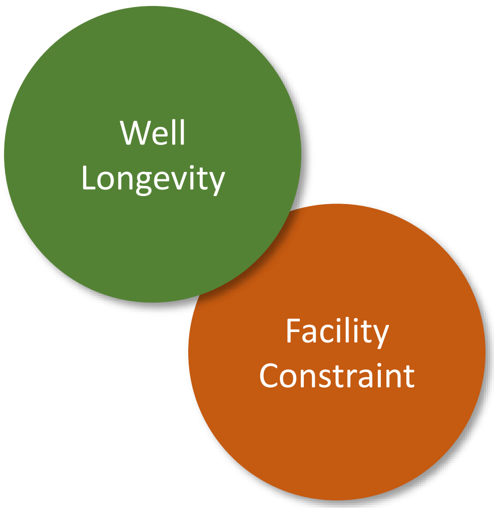


Source: mtja.org

The Objectives of Our Operations

- Objectives
  - Meet buyer's demand (we have a dedicated buyer):
    - Daily sales gas nomination (fluctuating)
    - CO_2 specification
  - Meet unit partners' demand:
    - Production meets agreed capital expenditure (CAPEX) ratio
  - Ensure longevity of wells
    - Be conservative in changing choke size (especially for sensitive/cyclic wells)
  - Meet facility constraint
    - Facility capacity in handling produced water
    - Facility capacity in handling produced sand





Formulating The Objectives As An Optimization Problem (1)

Buyer's requirement

Sales gas production (MMscfd)

Error = Demand - Base

$$\epsilon_S = |S_T(t) - S_B(t)| \leq \epsilon_T$$

CO_2 specification

$$x_T^o(t) = \frac{\sum_{i=1}^{N} G_i^o(t) x_i(t)}{\sum_{i=1}^{N} G_i^o(t)}$$

Weighted Average CO_2

$$x_T^o(t) \leq x_{T,\max}$$

Facility constraints

Sales = f(Gross Rate, Feed CO_2)

$$S_i(t) = G_i(t)\,\underbrace{\left(\alpha\big(y_T(t)\big)x_i + \beta\big(y_T(t)\big)\right)}_{\text{Shrinkage factor } (CO_2 \text{ removal})}$$

Shrinkage factor (CO_2 removal)

Flare + Membranes

http://dreamstime.com/royalty-free-stock-photo-flare-boom-nozzle-fire-offshore-oil-rig-image28254785

Formulating The Objectives As An Optimization Problem (2)

- Ensure profitability of unit partners

$$\epsilon_S = |S_T(t) - S_B(t)| \leq \epsilon_T$$

1st Unit Partner's requirement

$$\epsilon_1 = |u_1 S_B(t) - S_1|$$

2nd Unit Partner's requirement

$$\epsilon_2 = |u_2 S_B(t) - S_2|$$

Formulating The Objectives As An Optimization Problem (3)

- Taking care of sensitive wells

Sensitive wells

$$\min\left(W_{G,i}\right) = \max\left(W_{G,i}\right) = W_{G,i}(t-1) = W_{G,i}(t)$$

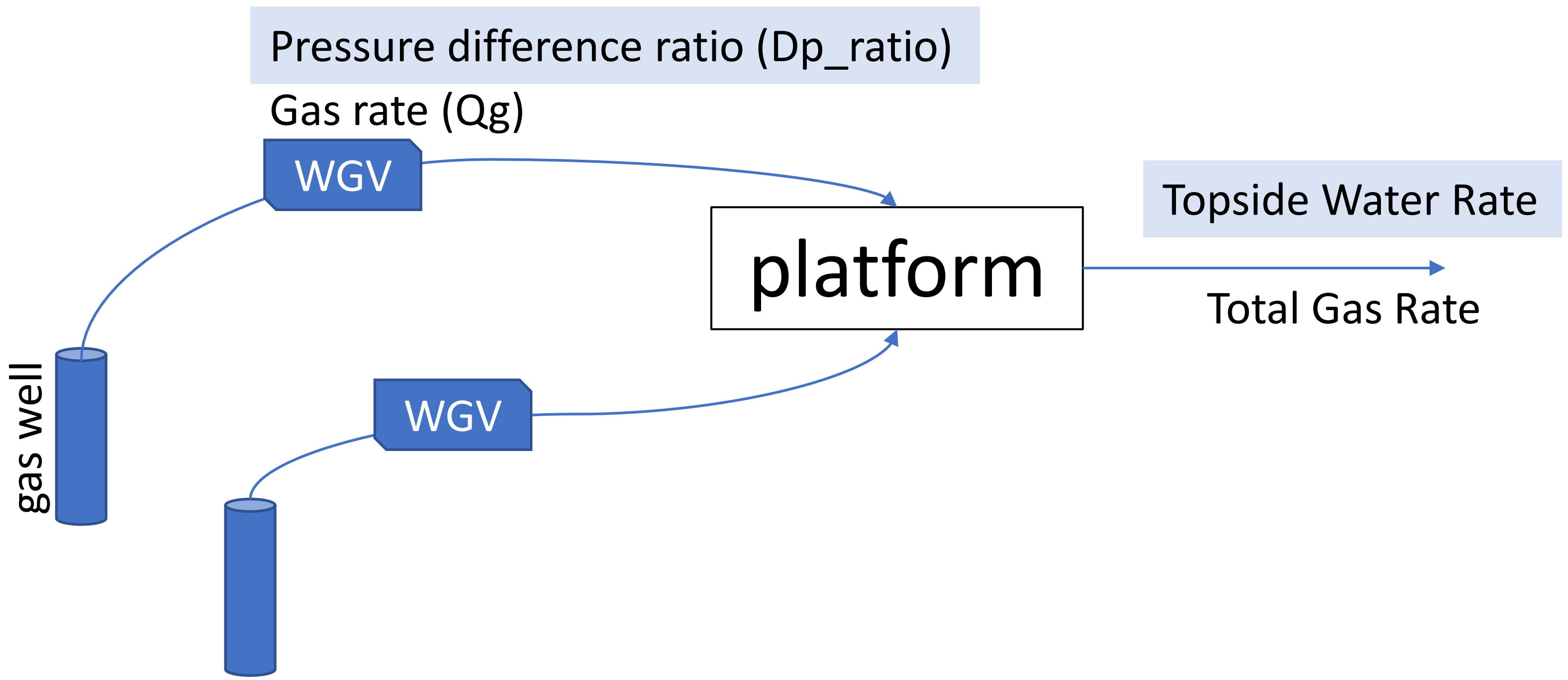
Non-sensitive wells

$$\min\left(W_{G,i}\right) \leq W_{G,i}(t) \leq \max\left(W_{G,i}\right)$$

Major Constraints

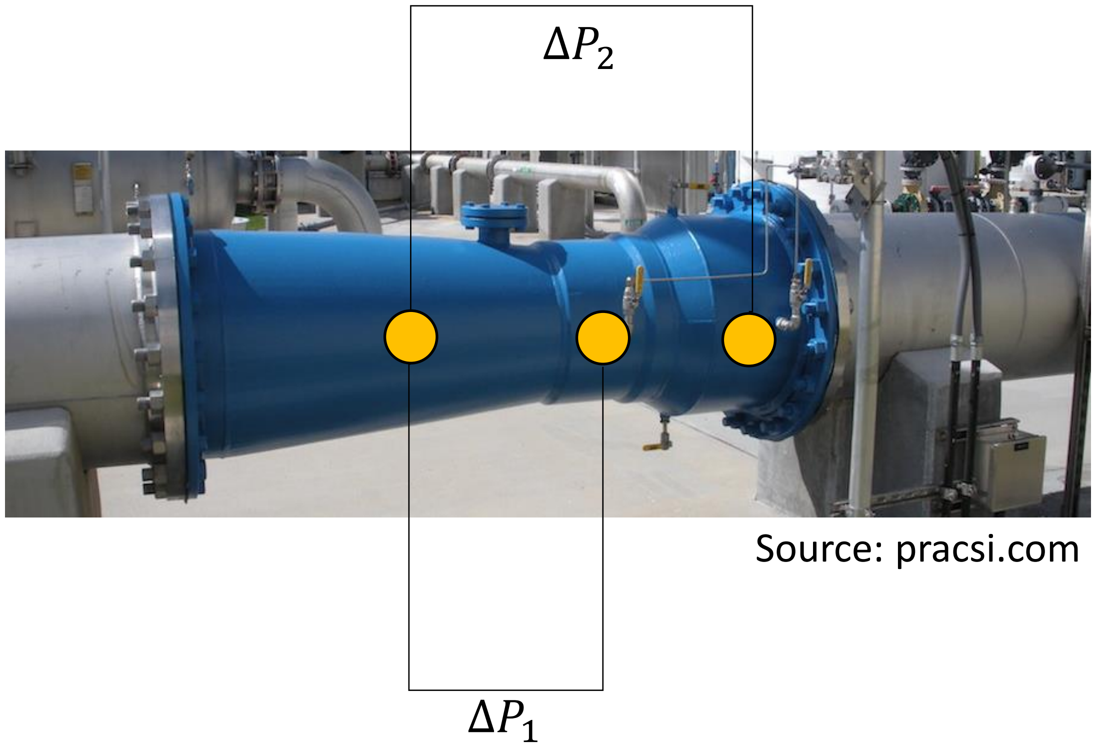
- Facility handling capacity
  - Water production
  - Sand production
- Issue: Limited information (measurements)
  - Water production rate for each well?
    - Available sensors: Wet Gas Venturimeter, Temperature
  - San production rate for each well?
    - Available sensors: Acoustic Sand Device

Identifying Water Producing Wells



WGV: wet gas venturi meter

Wet Gas Venturi Meter



Source: pracsi.com

$$DP\ Ratio = \frac{\Delta P_2}{\Delta P_1}$$

Converting DP ratio to Water Rate

$$Q_w = f(Q_g, CGR, DP\ Ratio, \rho_g, \rho_w, \rho_c)$$

Assumption (throughout all wells):

- Constant CGR
- Constant fluid densities

Leeuw, R.C. (1997). Liquid correction of venturi meter readings in wet gas flow. North Sea Flow Measurement Workshop.

Objectives

- Determine well-by-well water production rate using:
  - Pure AI approach
  - Simple material balance + AI approach
  - Time series approach

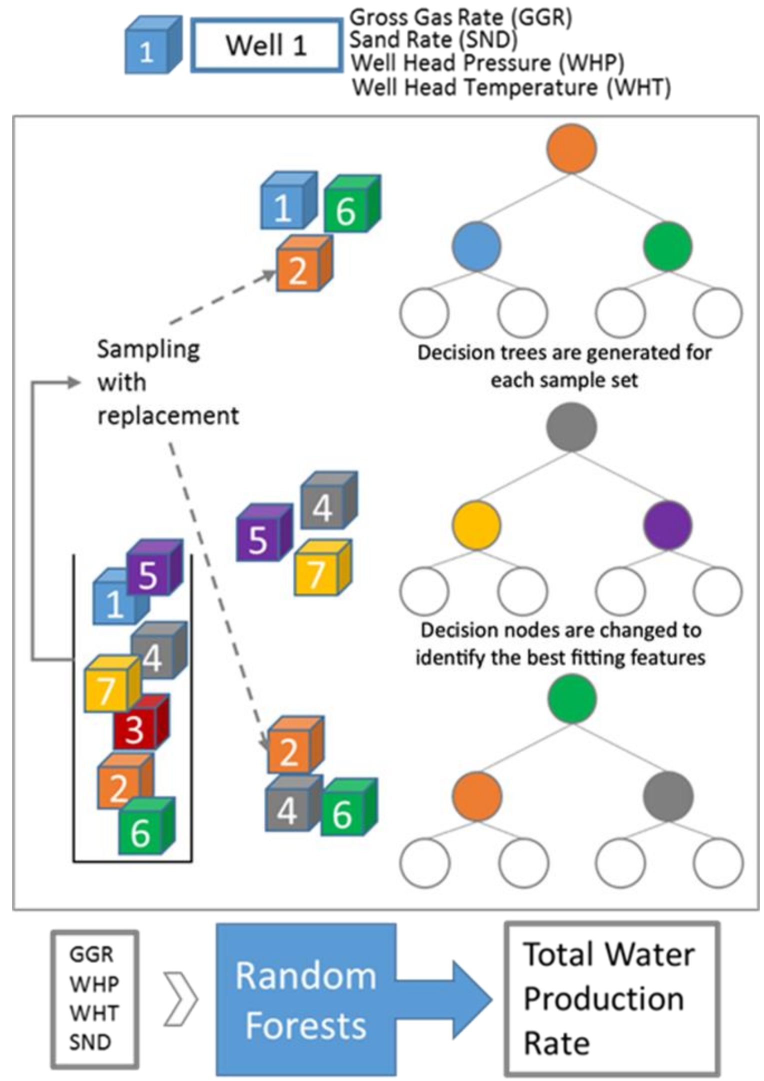
- Develop AI apps that directly take input data from the database server.

Pure AI Approach

- Random Forests for regression
  - Supervised learning
  - Ensembles of decision trees
  - Good for data with large input features and fewer samples
  - Shows ranking of input features

Well parameters → Random Forests → Topside Water Rate

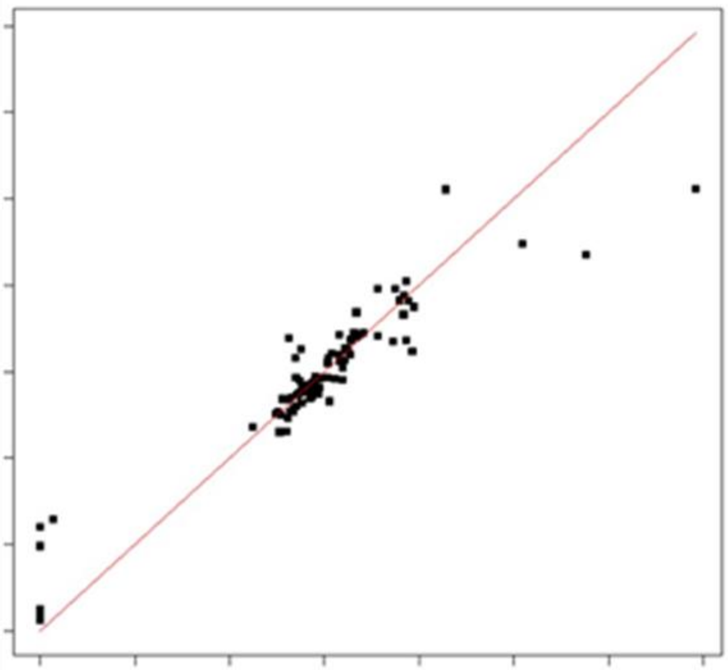
Input | Output



Random Forests Results

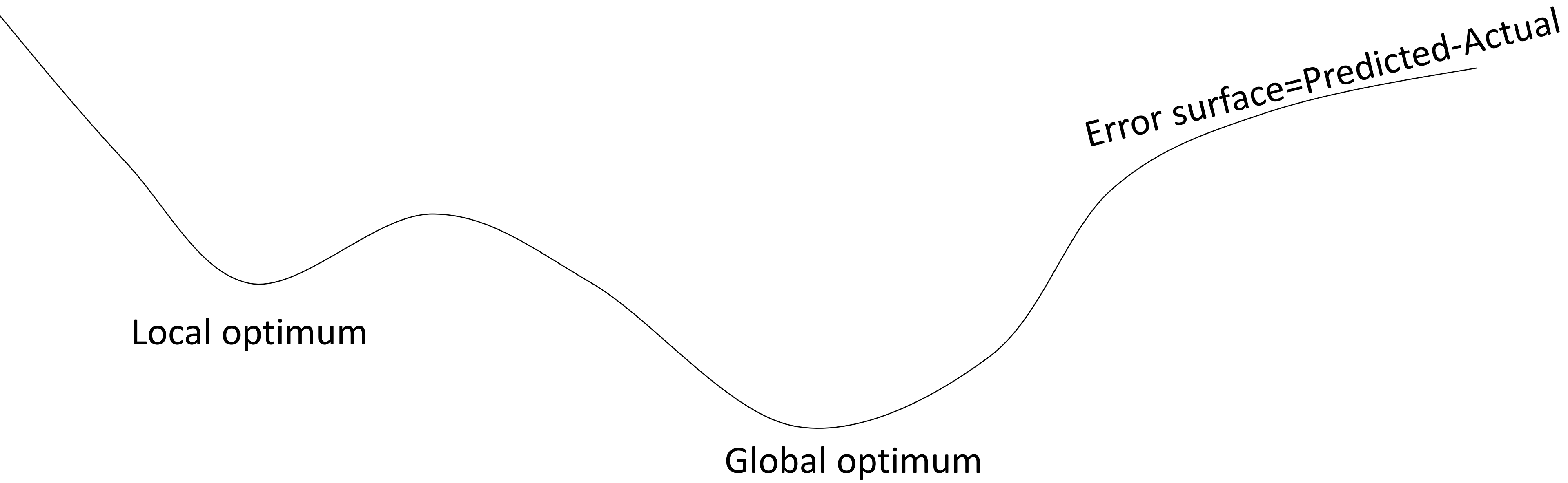
- Great predictive capability
- Shows ranking of input features, i.e. well parameters

Well	Parameter	% Influence
15	WHT	8.9
9	GGR	8.2
15	WHP	7.1
89	WHP	6.6
16	WHP	6.4
71	GGR	6.3
11	WHP	6.0
9	WHT	5.8
71	WHT	5.6
37	WHP	5.6



Another Approach: Simple Balance + AI

- Goal: Solve Water/Gas Ratio (WGR)
- Genetic Algorithm is known to solve for global optimum



Description of Material Balance (1)

$$\mathcal{W}_k(t) = \omega_k G_k(t) \quad \Rightarrow \quad \mathcal{W}(t) = \sum_k \mathcal{W}_k(t)$$

Well by well water rate

Total Water rate

Where:

- $\mathcal{W}_k(t)$ is water production rate of k^{th} well at time t, measured in bbld (barrels per day)
- ω_k is WGR, in bbld/mmscfd
- $G_k(t)$ is gross gas production rate of k^{th} well at time t, in bbld.

Description of Material Balance (2)

Taking the gross gas rate for all wells,

$$\boldsymbol{G} = \{G_1(t), G_2(t), G_3(t), \ldots\},$$

the entire problem can be represented by:

$$\boldsymbol{G} \cdot \omega_k = \mathcal{W}(t)$$

Well gross gas

WGR

Total Water rate

Solving with Global Optimization Method

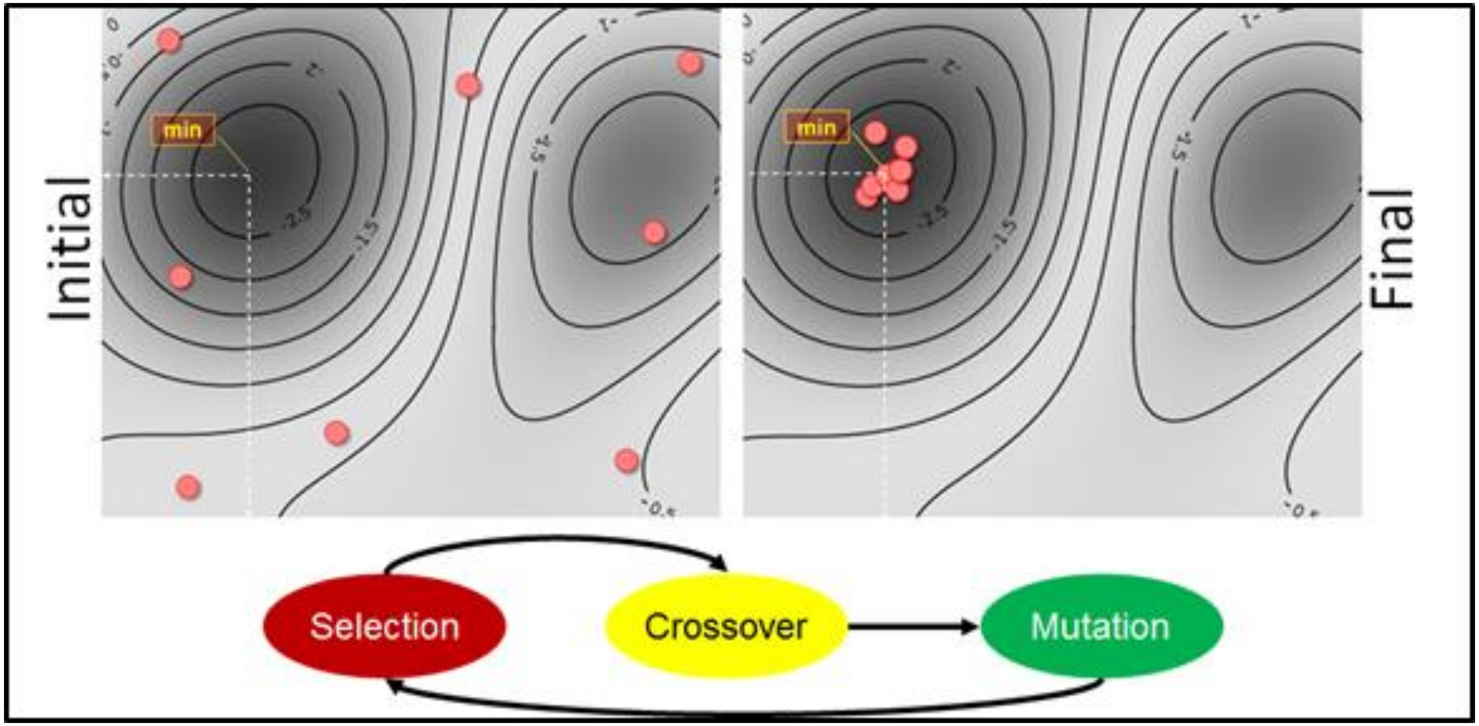
- Genetic Algorithm

$$\boldsymbol{G} \cdot \omega_k = \mathcal{W}(t)$$

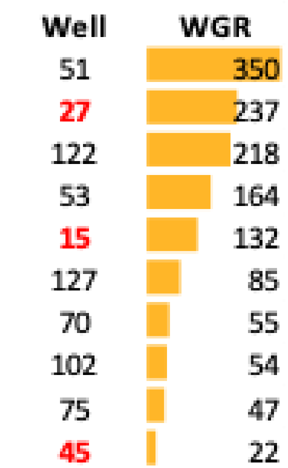
Well gross gas

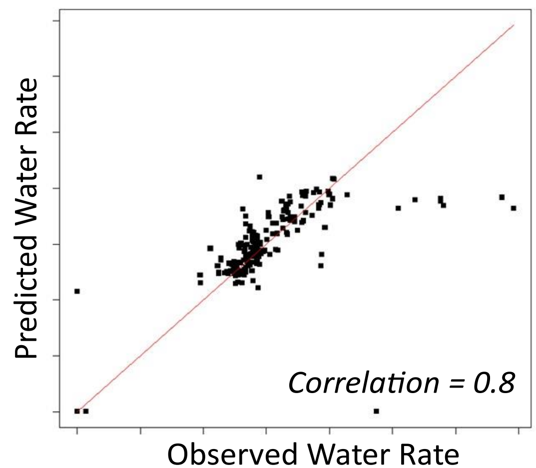
WGR

Total Water rate

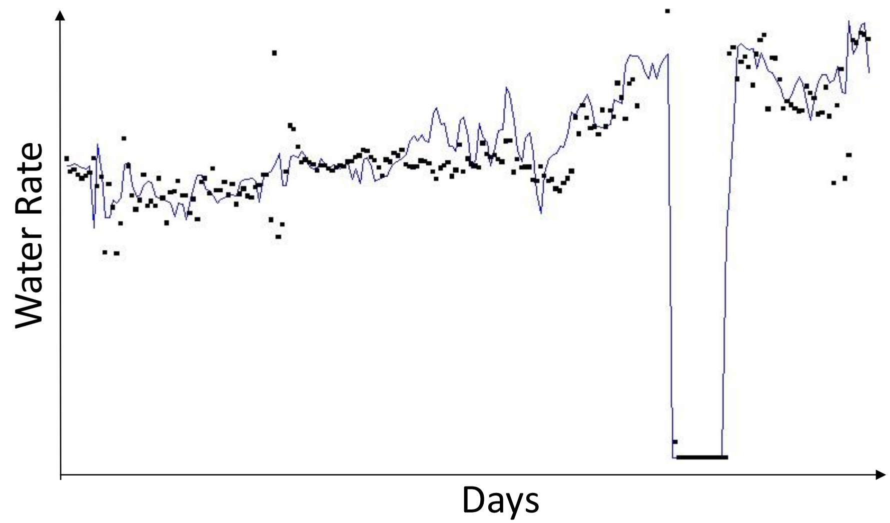


GA-based WGR





Predicted (Line) vs Observed (Dot)



Water Analytics: Time Series Approach

Instead of modeling this with machine learning,

$$f(a_1(t), a_2(t), a_3(t), \cdots, a_N(t)) \rightarrow y(t)$$

IN(t) OUT(t)

We took another approach,

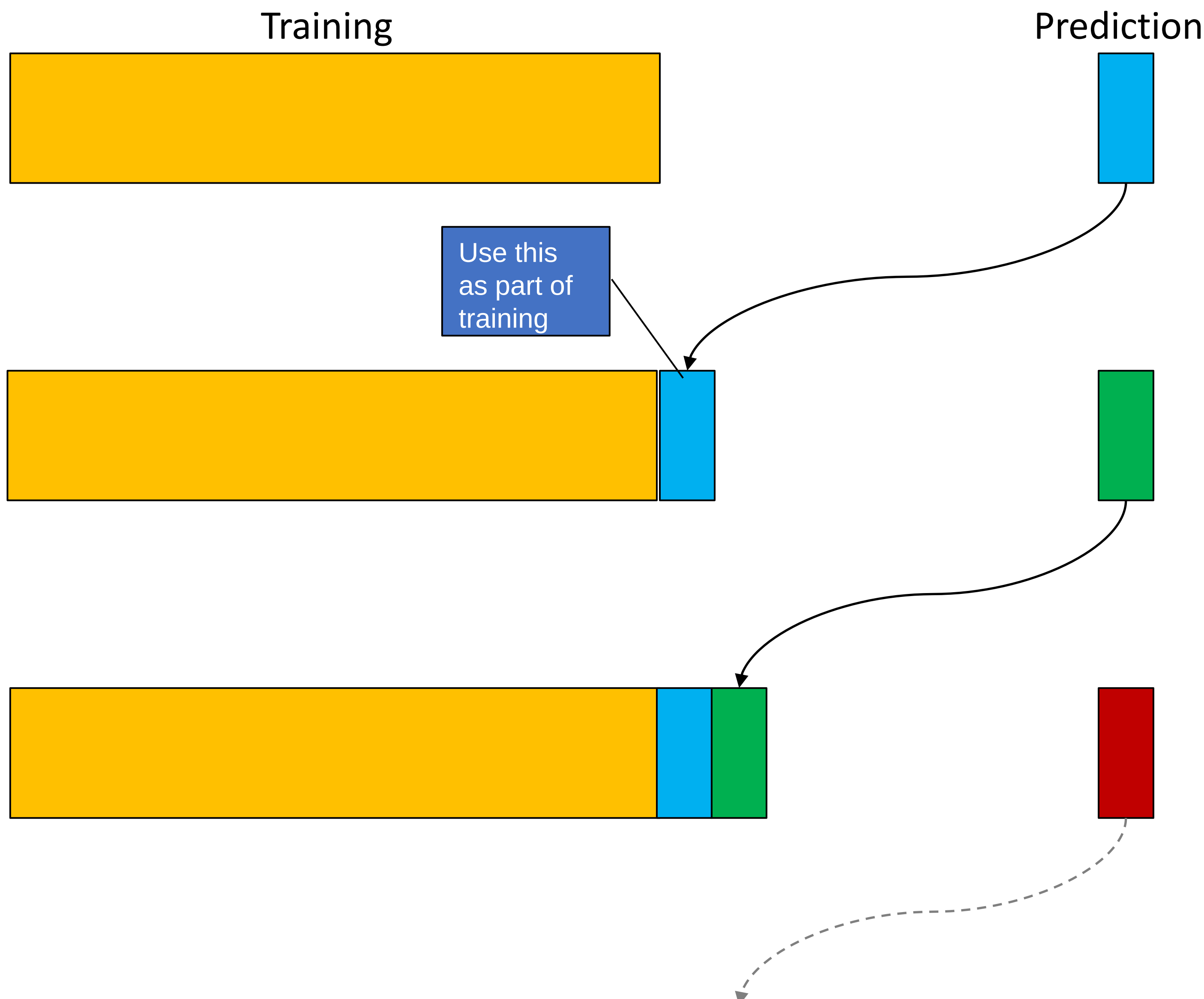
$$f(a_1(t), a_2(t), a_3(t), \cdots, a_N(t), a_1(t-1), a_2(t-1), a_3(t-1), \cdots, a_N(t-1), \cdots, a_1(t-k), a_2(t-k), a_3(t-k), \cdots, a_N(t-k)) \rightarrow y(t)$$

IN(t) IN(t-1) IN(t-k) OUT(t)

Why do this?

Intuitive example: Due to the loss of pressure in the reservoir, the same choke opening today will not yield the gross gas rate of yesterday.

Walk-In Validation Concept



Experiments

- ML models: Random Forests, Gradient Boosting (XGBoost)

Type	Elements
Input	choke (t, t-1, ...)
	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	Random Forests

Type	Elements
Input	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	Random Forests

Type	Elements
Input	choke (t, t-1, ...)
	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	XGBoost

Type	Elements
Input	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	XGBoost

Type	Elements
Input	temp (t, t-1, ...)
	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	XGBoost

Type	Elements
Input	temp (t, t-1, ...)
	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	XGBoost

Time Series with Walk-In: Results (1)

Type	Elements
Input	temp (t, t-1, ...)
	dp ratio (t, t-1, ...)
	water (t-1, t-2, ...)
Output	water (t)
Model	XGBoost

After numerous trials,

XGBoost with Temperature, DP Ratio, and Historical Topside Water seems to be promising.

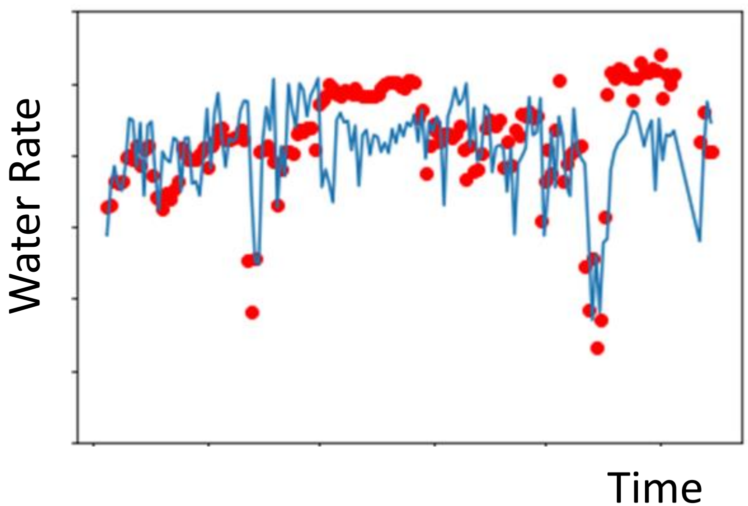
Time Series with Walk-In: Results (2)

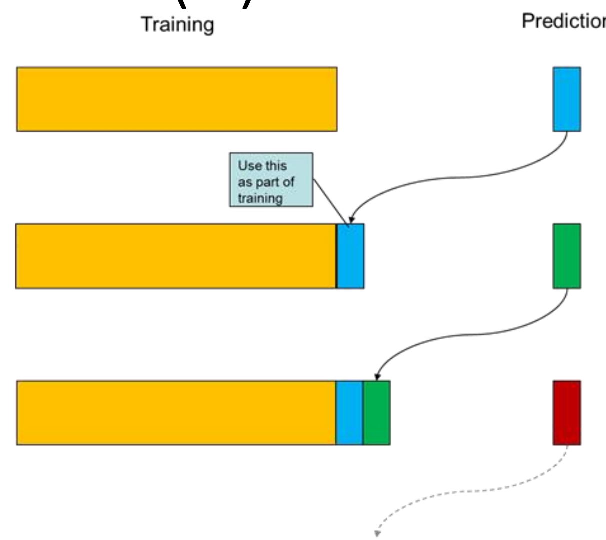
```
[1252]: mse = ((y_test - y_pr)**2).mean()
        Rsq = np.corrcoef(y_test,y_pr)

        print("RMSE = ", np.sqrt(mse), " bbl/day")
        print("R2 = ", Rsq)
```

```
RMSE = [redacted] bbl/day
R2 =  [[1.         0.43247048]
 [0.43247048 1.        ]]
```

```
[1253]: plt.scatter(X_test_date, y_test, color="red")
        plt.plot(X_test_date, y_pr)
        plt.xticks(rotation=90)
        plt.ylim([10000,22000])
        plt.show()
```





test_7.ipynb

```
[ ]: # perform walk-forward validation
     # X_train, y_train, X_test, y_test
     for j in range(0, len(y_pr)):
         temp = np.array(X_test[j,:]).copy() # take j^th row of X_test

         for k in range(0,j+1):
             col_idx = j+k*ncol_orig

             if col_idx<=ncol_offset:
                 temp[col_idx] = y_pr[j-k].copy() # offset: replace true water rate with predicted water rate
                 #print("j+k*ncol_orig = ", j, "+", k, "*", ncol_orig, "=", j+k*ncol_orig)
             else:
                 break

         y_pr[j] = regressor.predict(np.array([temp])) # predict water rate based on j^th row of X_test

         # update training set for walk-forward validation
         X_train = np.vstack([X_train, temp])
         y_train = np.hstack([y_train, np.array(y_pr[j]).copy()])

         # retrain model
         regressor.fit(X_train,y_train)

         print("j = ", j)
```

Sand Analytics (1)

- We have installed acoustic sand device.
- The vendor provided the sand rate for each well based on proprietary equations.
- Sum of all sand rates did not match with the total sand produced.

https://www.clampon.com/wp-content/uploads/2013/04/particle_monitor_2_500px.jpg

Sand Analytics (2)

- Formulation: Given *N* wells,

$$c_1 w_{1,ASD}(t) + c_2 w_{2,ASD}(t) + \cdots c_N w_{N,ASD}(t) = \sum_i c_i w_{i,ASD}(t) \rightarrow Q_{sand}(t)$$

Optimizer: GA Islands

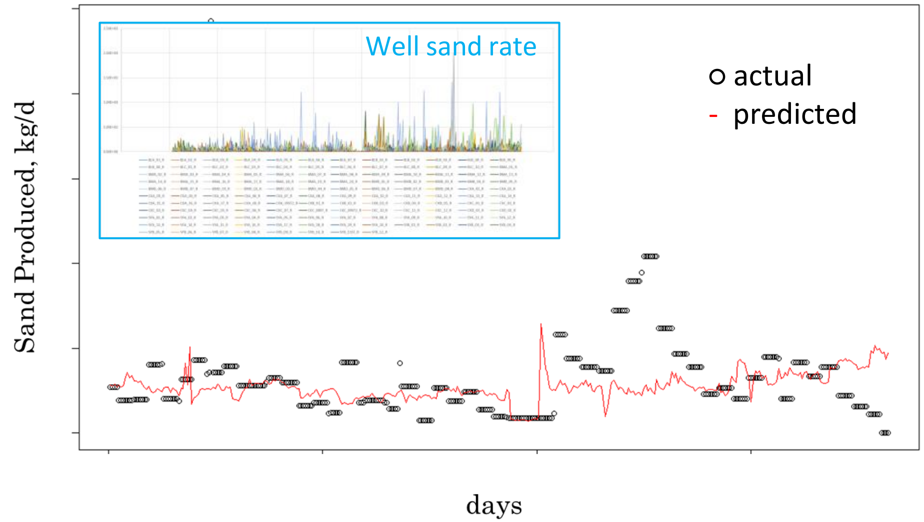
Challenges:
Multiple sand catch pot manually sampled at non-synchronous schedule.
How to derive the daily sand rate $Q_{sand}(t)$?

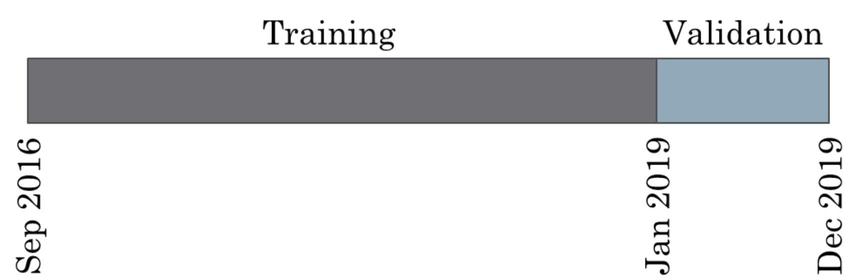
Sand Analytics (3)

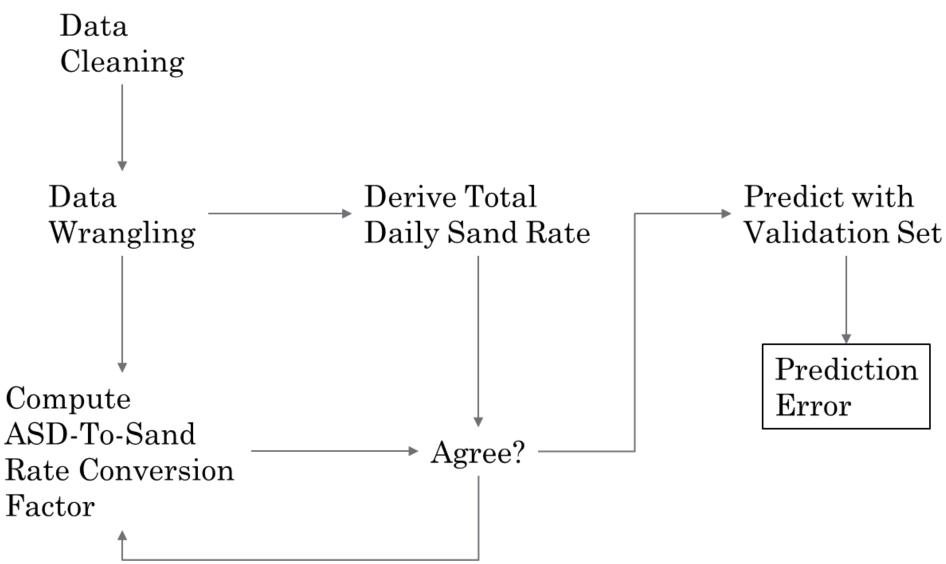
Objectives

- Develop a computer program to derive total daily sand rate
- Develop a AI-based module to convert ASD (Acoustic Sand Device) signal of each well to a sand rate that obeys the total daily sand rate

Predicted total sand production (2019)







Conclusions

- Many different ML-based approach to quantify sources of water and sand.
- Computing water gas ratio (WGR) is highly interpretable to engineers. However, in reality, WGR for a well is not a constant value.
- The simple balance model (i.e. computing WGR) reflects good prediction for the training data, but not the test data. Hence, not reliable enough for prediction.
- Random Forests model can predict future water rate, and at the same time it can rank the importance of each well measurements. But, the engineers find it hard to interpret.
- Using time series method to predict future water rate, XGBoost outperformed Random Forests significantly. For daily dataset, XGBoost could reliable predict 3 to 6 months onto the future. Expect a low prediction accuracy when there is a facility shutdown.
- Converting acoustic signals to sand rate is quite reliable with a linear factor. The factor can be solved using Genetic Algorithm, although computationally expensive. Expect a low prediction accuracy when there is a facility shutdown.

Thank you.