Jacobs Challenging today. Reinventing tomorrow.

Machine Learning in Water

Coagulation Optimization

Benedicte Diakubama

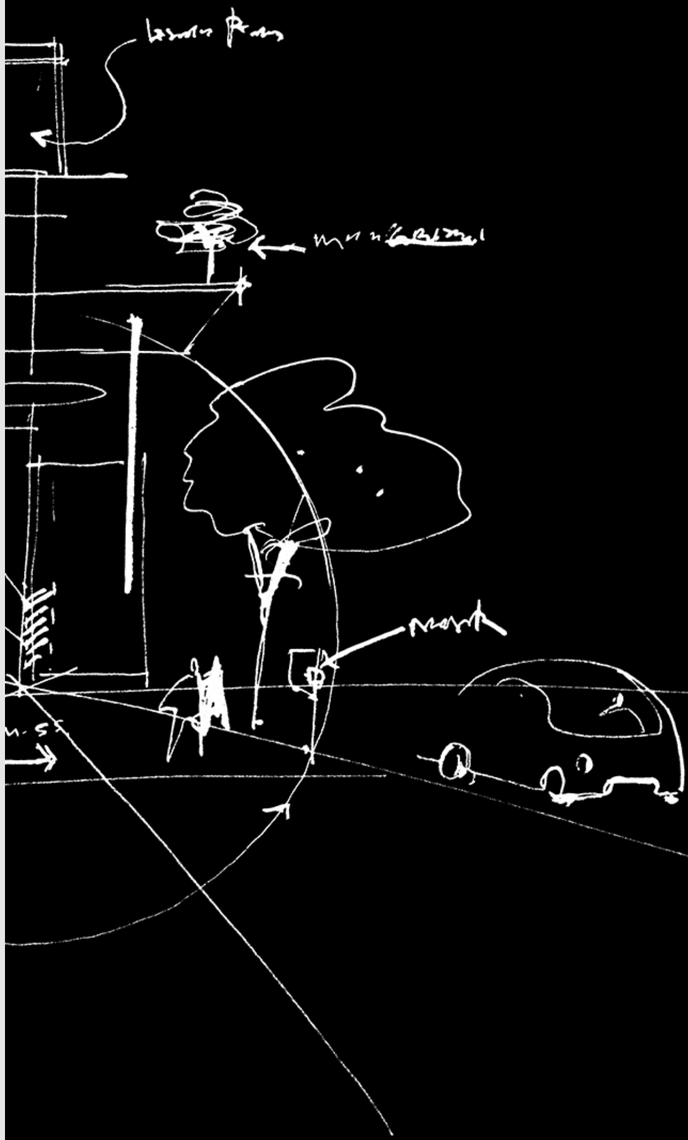
Background

- Machine Learning
- Coagulation

Case Studies

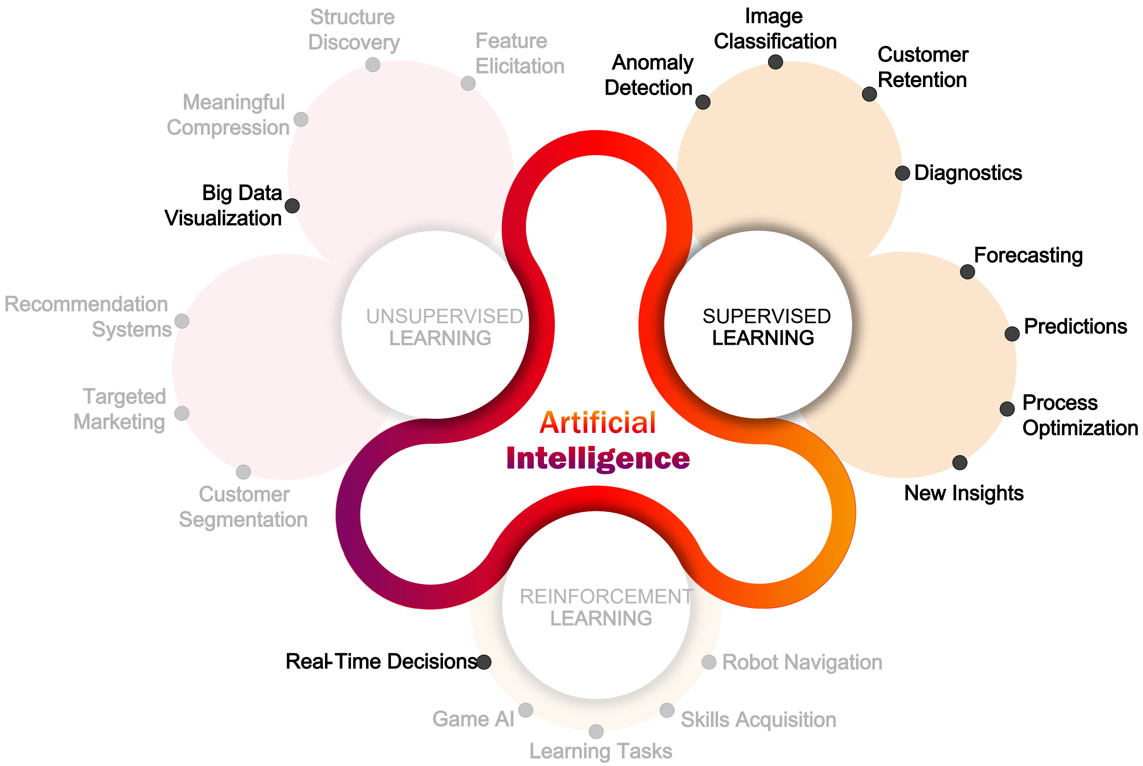
- Woodland Davis
- Melbourne Water

Lessons Learned



Background

Machine Learning

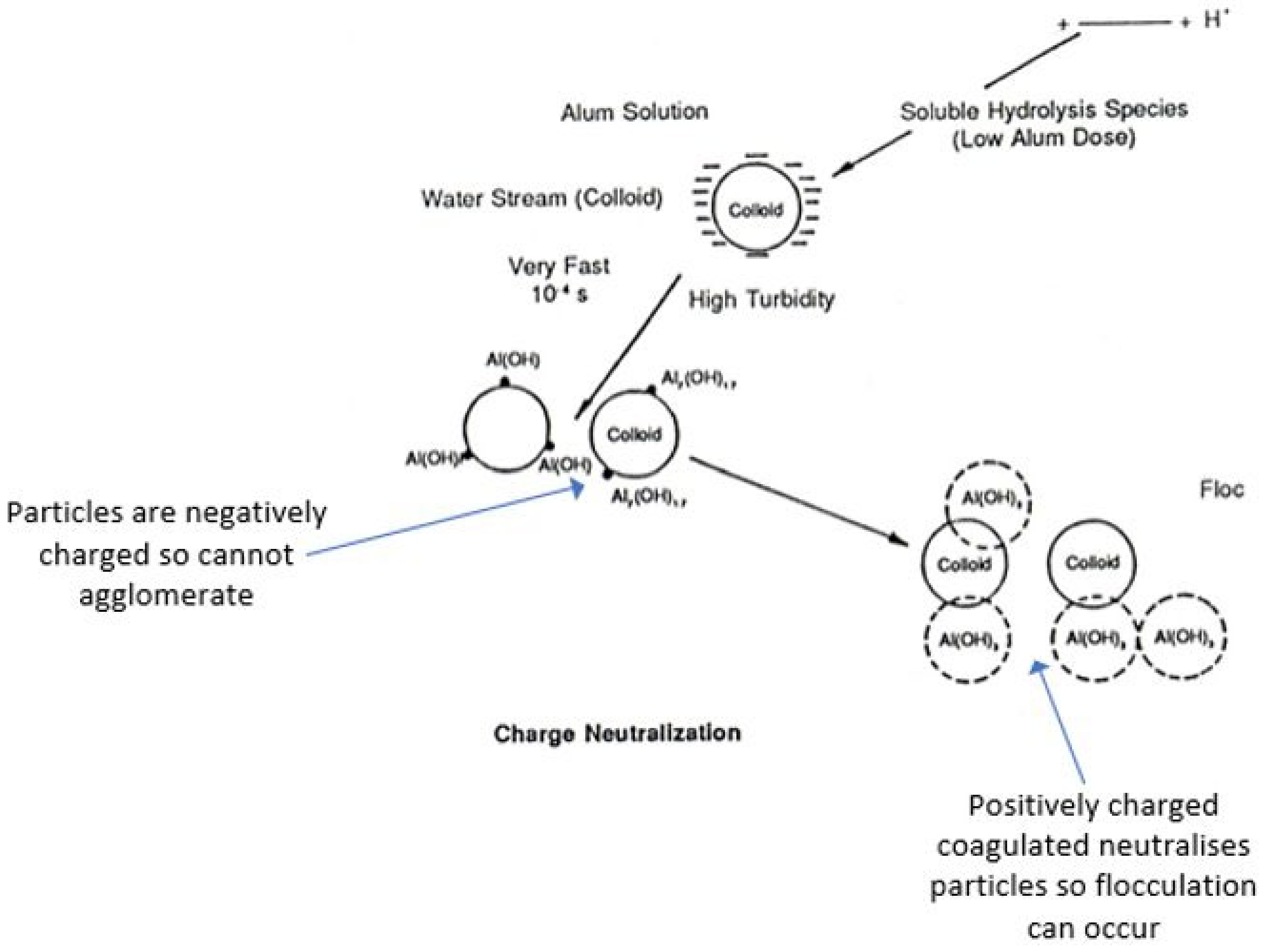


AI/ML Benefits

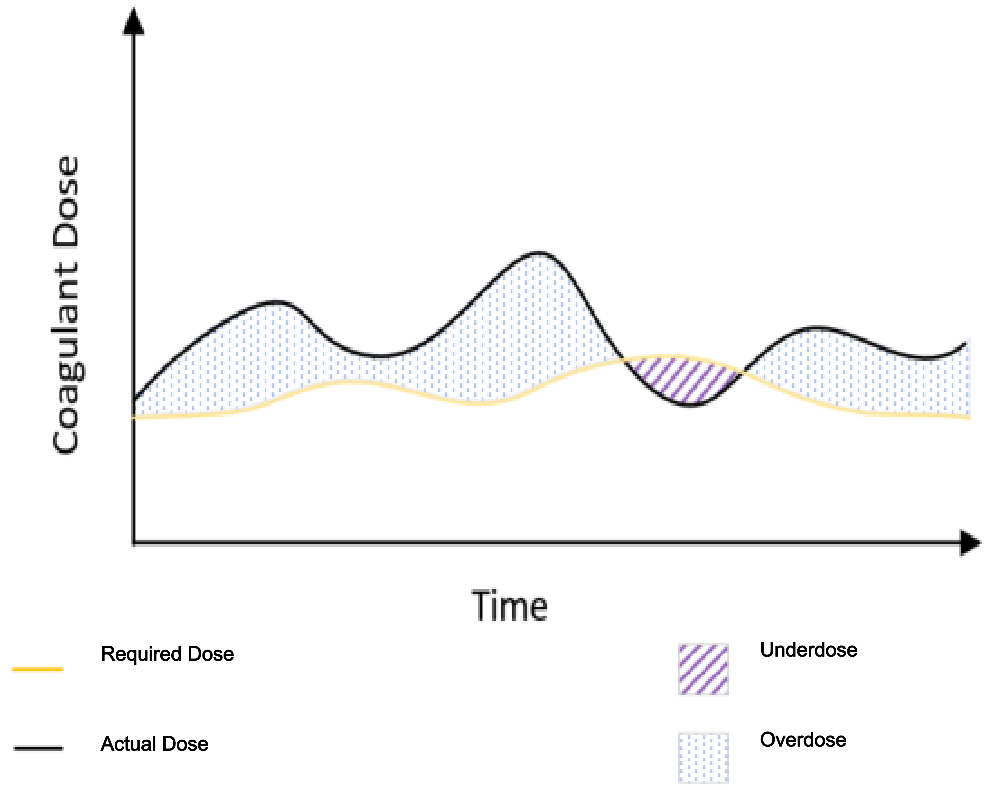
- Make our lives easier
  - Quickly analyze vast amount of data
  - Provide timely input for decisions
  - "Learn" and provide answers based on the historical data, not rules/equations/anecdote
- Identifying empirical relationships to deal with uncertainty and variability
- Fast calibration with online high frequency sensor data
- Quick adaptation to changes with the same resources
- 10-15% saving in coagulant dosing
- Increased confidence in operations- ability to see things ahead of time
- Saving in other chemicals, energy, and residuals

Treatment Process: Coagulation

- Chemical, positively charge metal salt
- Facilitates removal of:
  - Turbidity
  - Pathogens
  - Contaminants such as As & Fe
- Precipitation/ Charge Neutralisation mechanisms
- Impacted by:
  - Temperature
  - Ionic Strength
  - Alkalinity
  - Suspended and Dissolved Solids
  - pH
  - Surface charge



Why Optimizing Coagulation with Machine Learning ?



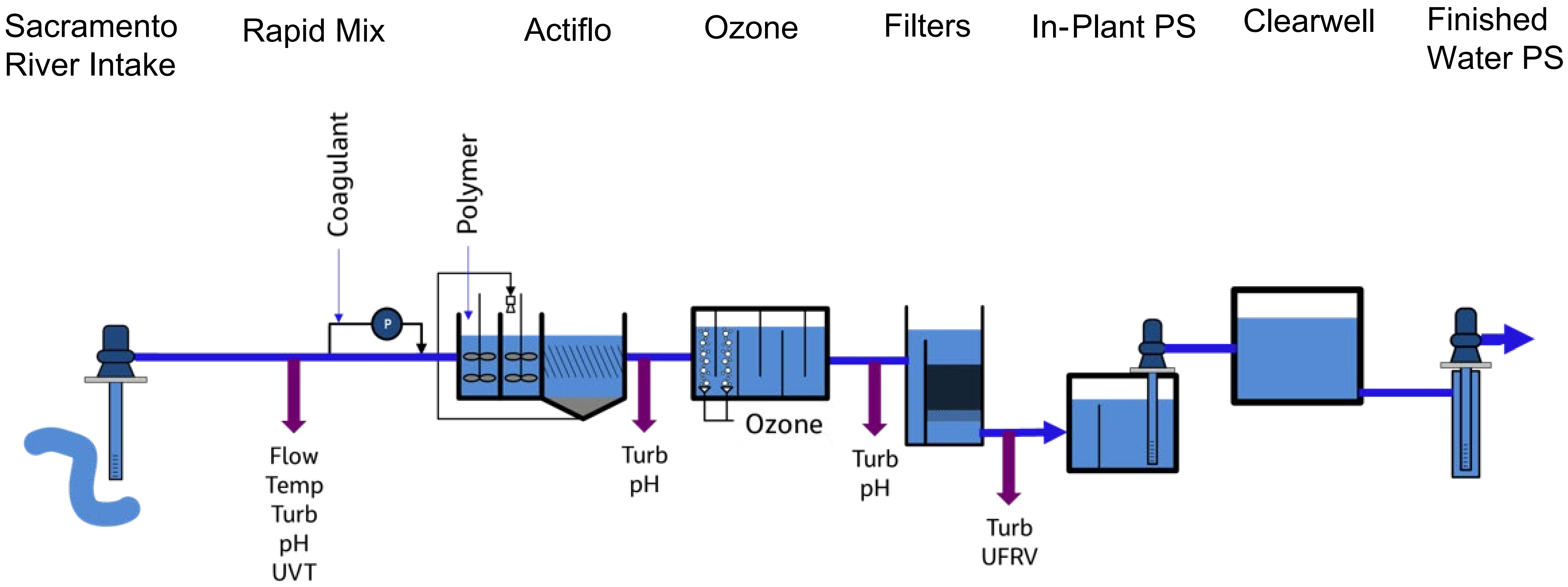
- There is no simple coagulation "equation"
- Long detention times make it difficult to react to changes
- Coagulation decisions are made based on experience, intuition, and trial and error
- Optimization can improve water quality, enhance efficiency, and lower costs

Machine Learning Goal: Optimize chemical doses and improve water quality

Case Study Woodland Davis

Regional Water Treatment Plant, California

Water Treatment Plant



Woodland Davis Regional Water Treatment Plant

- 30 MGD plant surface water treatment plant
- Began operation in 2016
- Located in Davis California
- Treats Sacramento River Water
- Treatment Process:
  - Coagulation with Ferric Chloride and Polymer
  - Sand ballasted clarification (Actiflo)
  - Ozone with Biological Filtration

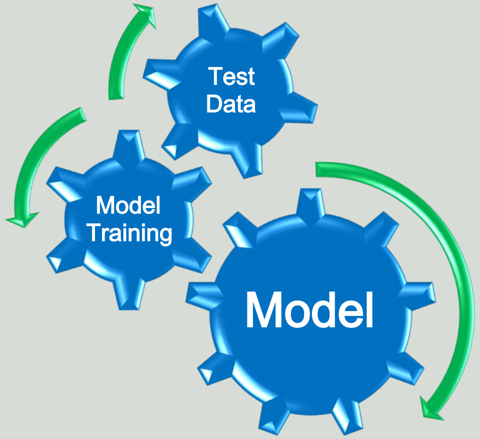
Machine Learning Goal: Optimize chemical doses and improve water quality

Implementation

STEP 1

Collect and Clean Data

STEP 2



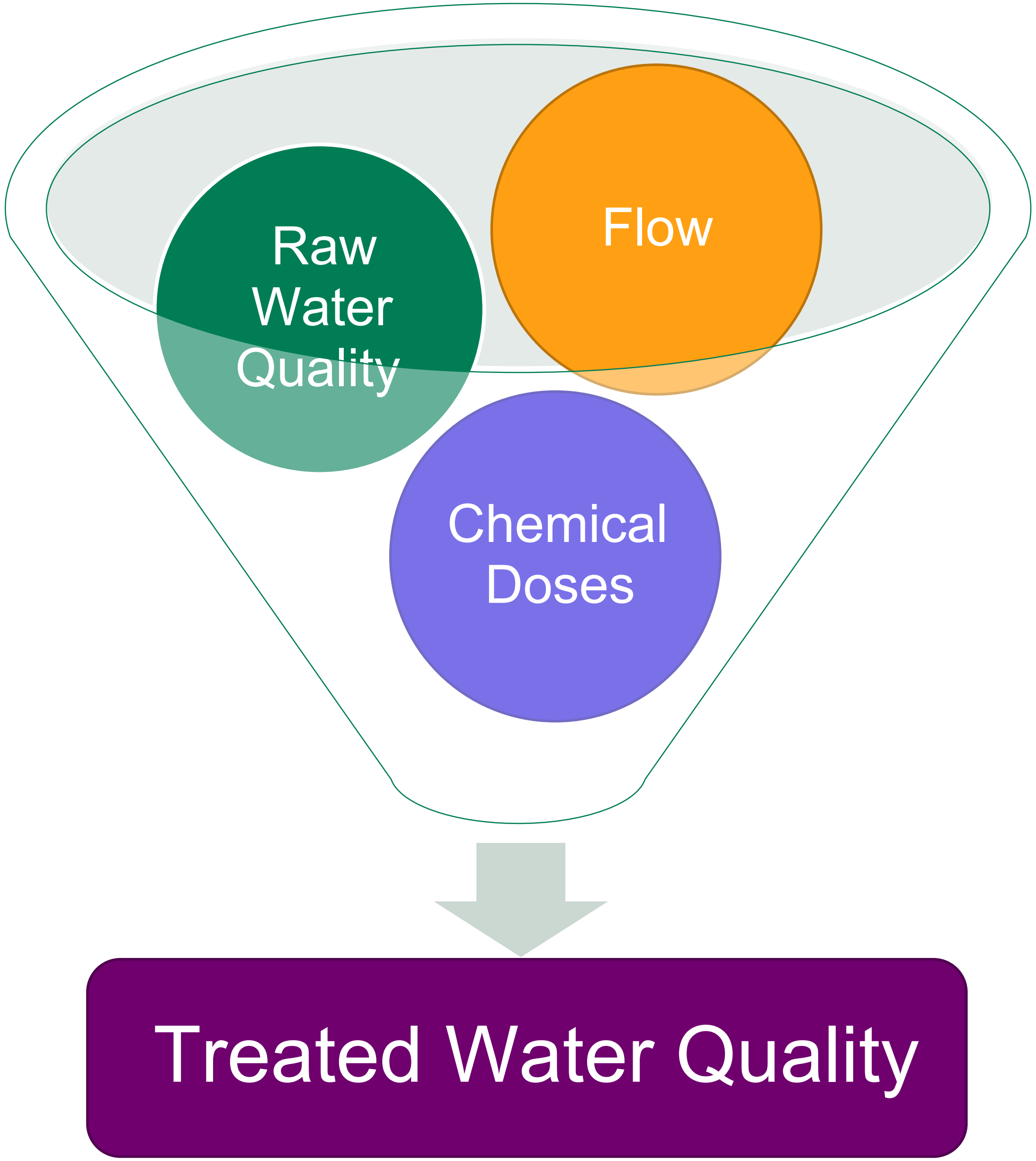
Develop Predictive Optimization Model

STEP 3

Create Web Dashboard

Input Data

- Model was trained with 2017-2019 online SCADA data
  - Flow
  - Raw Water Quality
    - Turbidity
    - UVT
    - pH
    - Temperature
    - Alkalinity
  - Chemical Doses
    - Ferric
    - Polymer
- Online raw water organics data critical to coagulation prediction



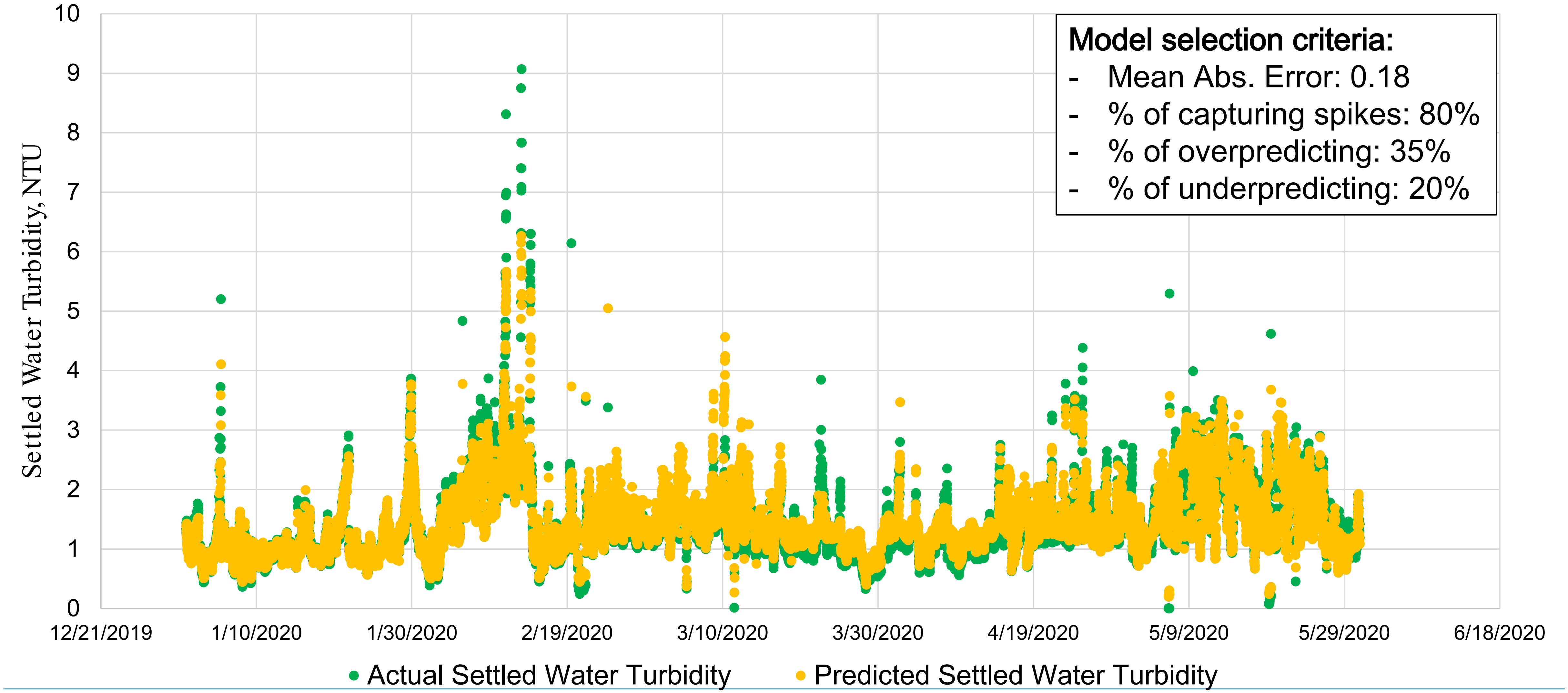
Predicted Optimization Summary

Month	Optimized Monthly Average Coagulant (mg/L)	Actual Monthly Average Coagulant (mg/L)	Cost Savings ($/month)
1	22.6	25.1	$4,400
2	26.2	28.5	$3,800
3	19.0	20.8	$3,600
4	20.0	22.0	$4,500
5	18.6	20.8	$6,000

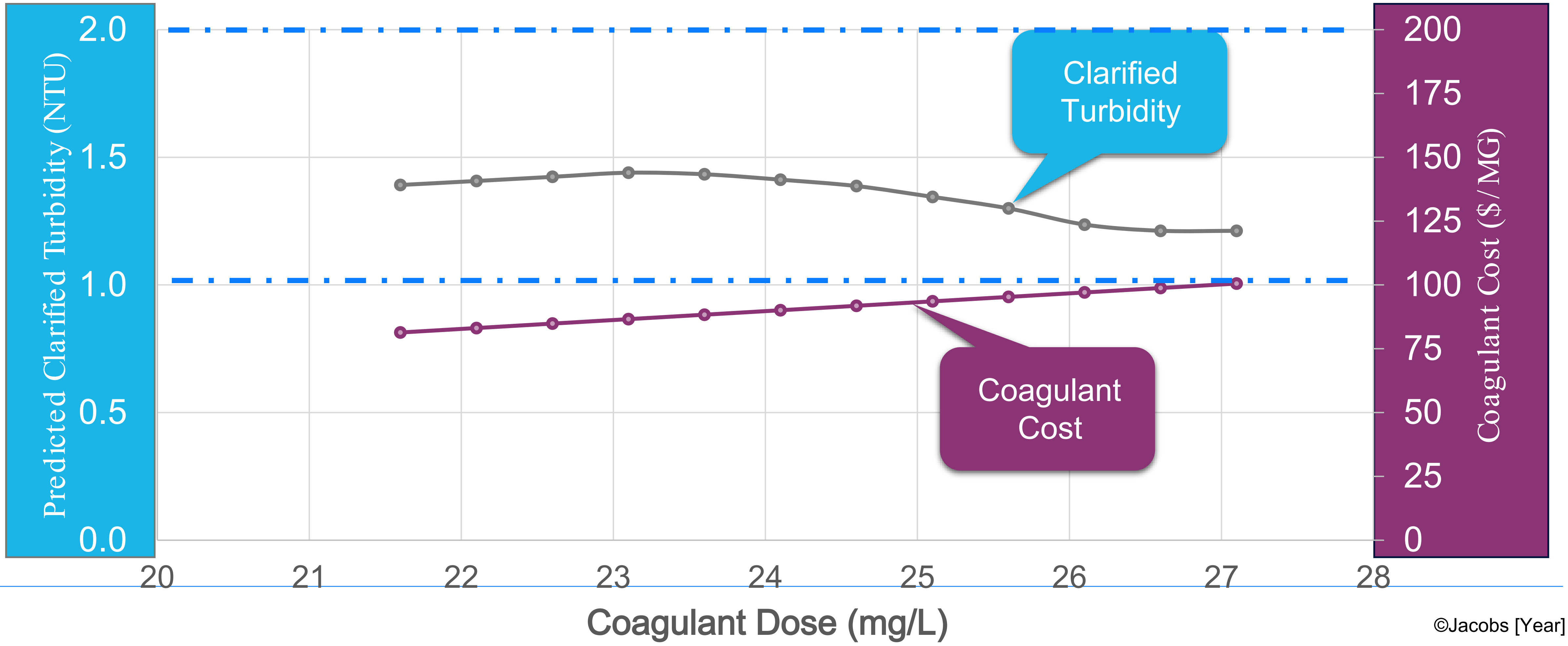
Average monthly cost savings 9%

Projected annual cost savings $54,000-$72,000

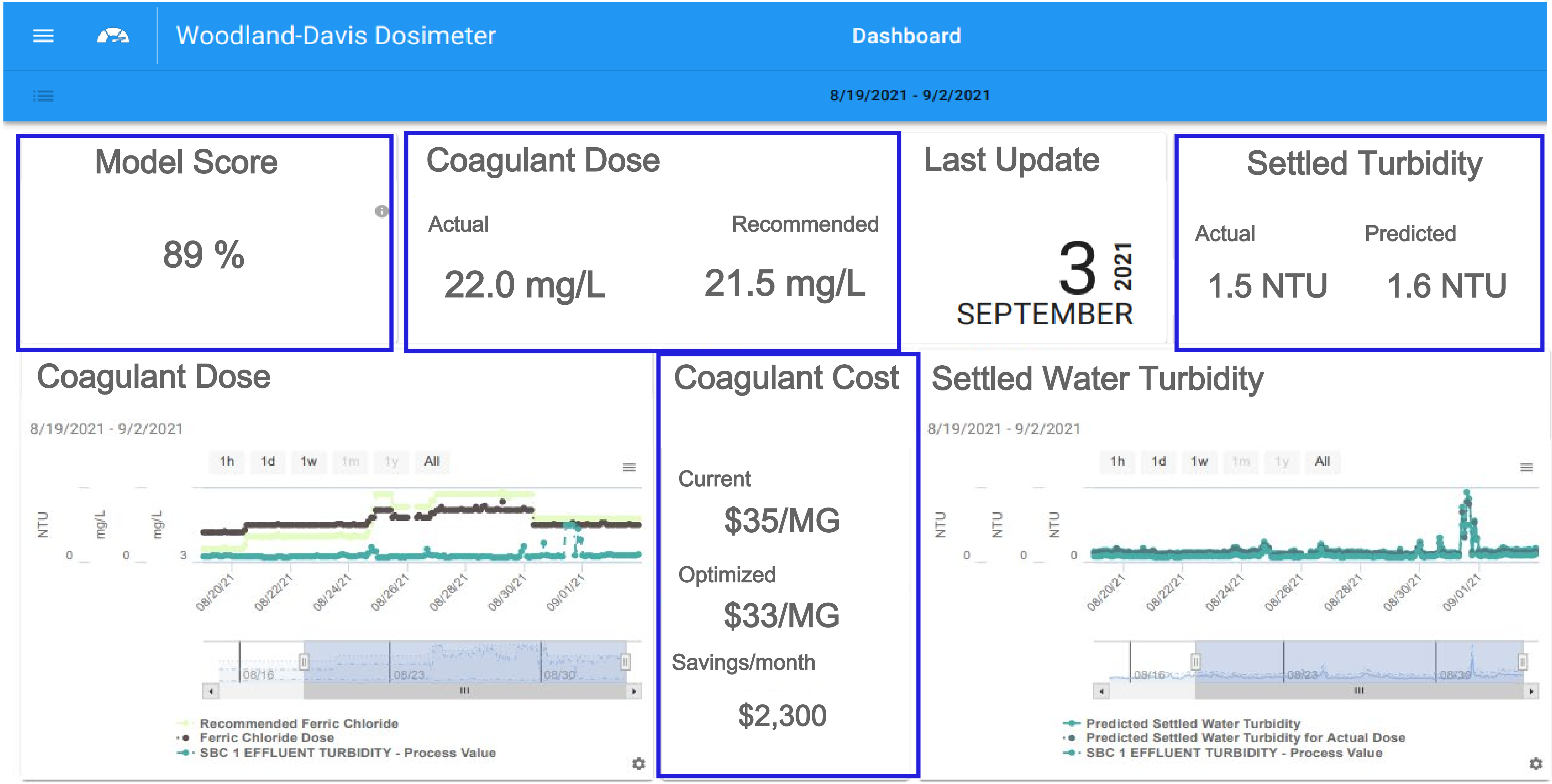
Trained Model Prediction



Optimization Algorithm



Real-time information at your finger tips



ear]

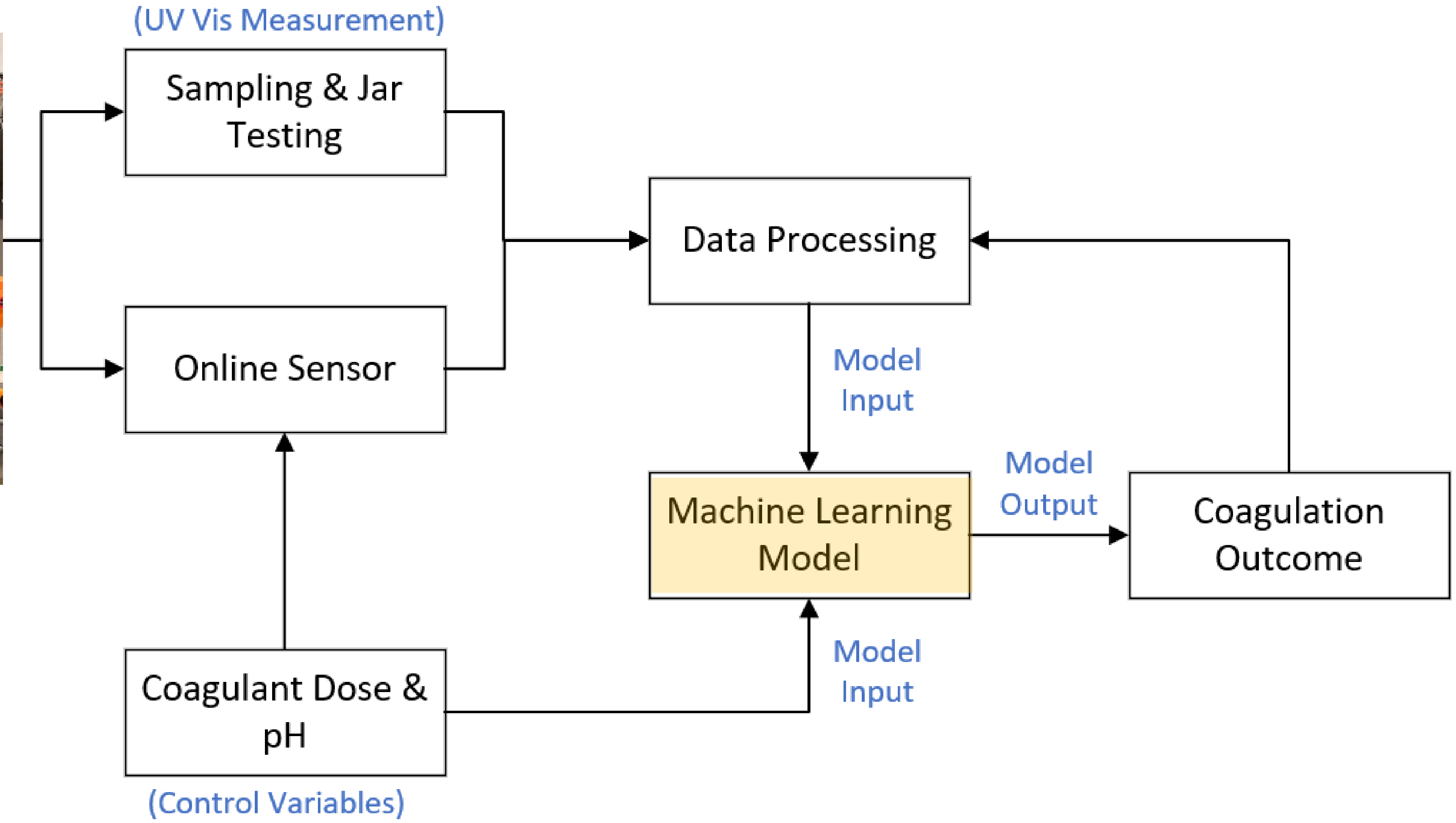
Case Study Melbourne Water

- 600 MLD (160MGD)
- Supplies ~30% of Melbourne's drinking water
- Treatment Processes:
  Conventional, clarification, dual media filtration
- Coagulant (alum) is flow paced

Birdseye view of Winneke WTP

Model Development

(Measure UV Vis Spectra, turbidity, pH, alkalinity, temperature)



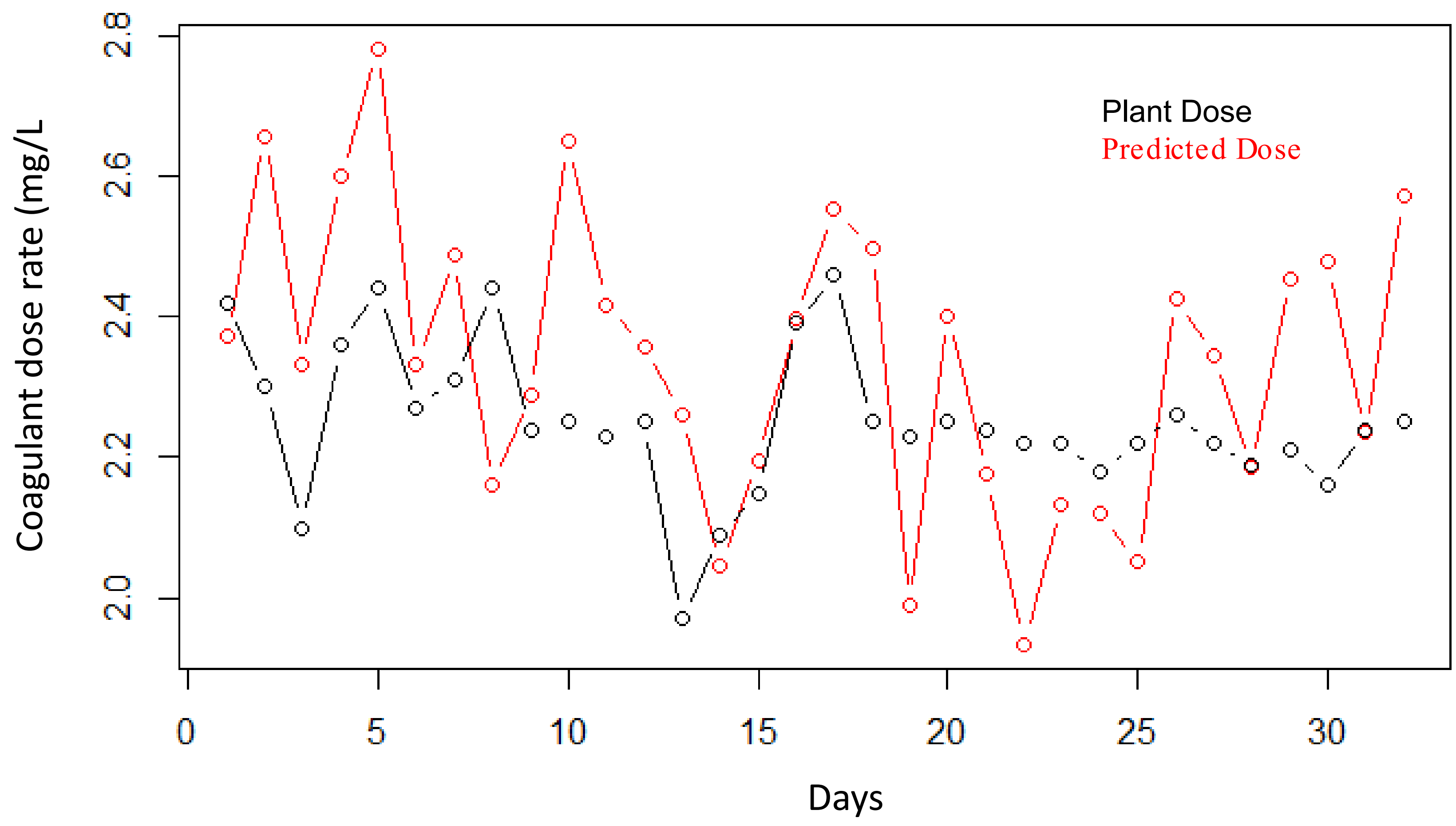
Optimization – Results (Cost Savings)

Day	Coagulant Dose Plant (mg/L as Al)	Coagulant Dose Model Optimized (mg/L)	% reduction
1	2.42	2.26	7%
2	2.3	2.20	5%
3	2.1	1.92	9%
4	2.36	2.14	9%
5	2.44	2.33	4%
6	2.27	1.99	12%
7	2.31	2.18	6%
8	2.44	2.26	8%
9	2.24	2.08	7%
10	2.25	2.16	4%
11	2.23	2.07	7%
12	2.25	2.07	8%
13	1.97	1.88	5%

Objective: Minimize coagulant use

- Coagulant Model predicts 8% reduction in Alum dose
- Savings of $160K AUD/year ($97K USD)

Optimization – Results (Maximize DOC removal)



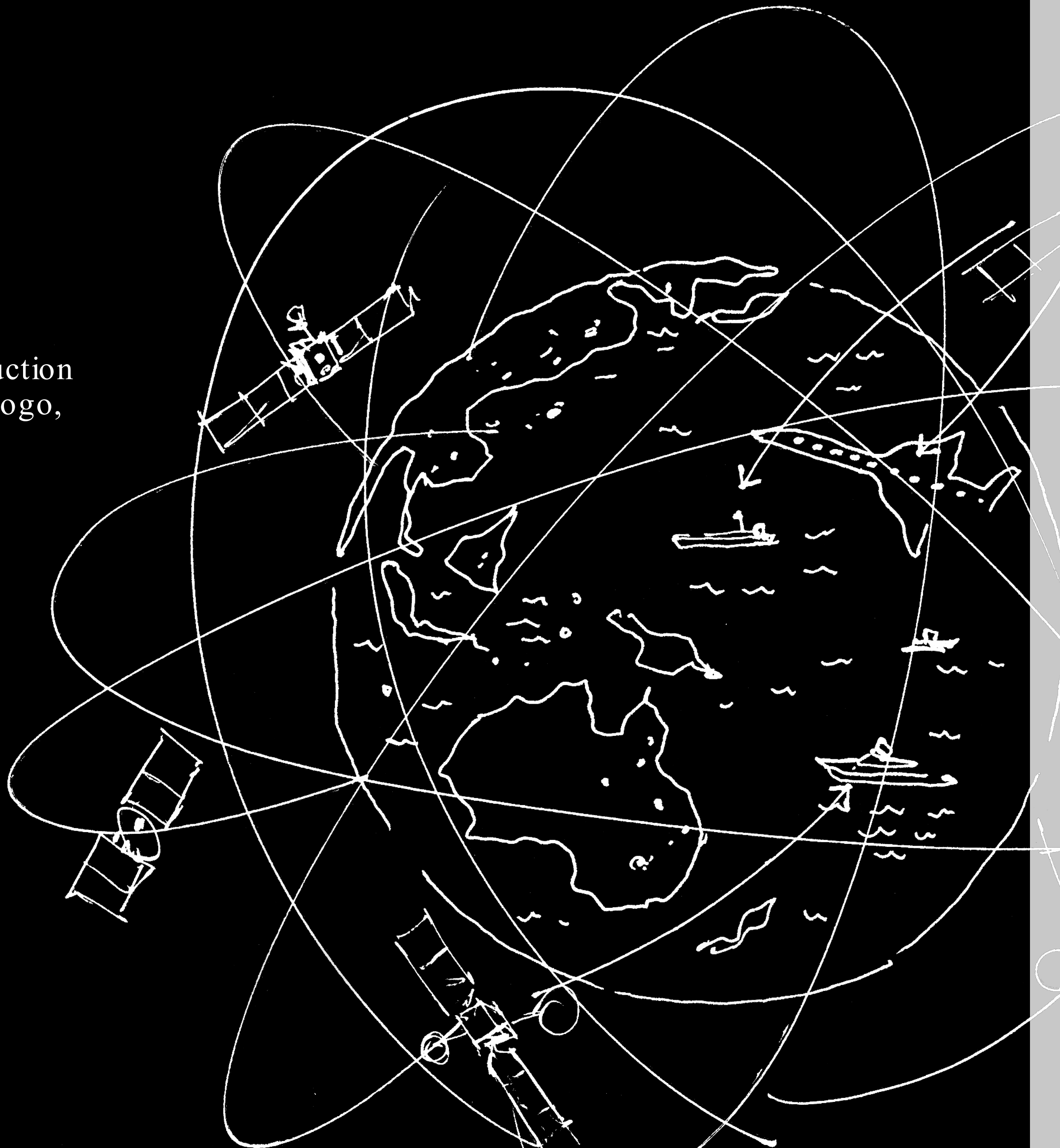
Objective: Maximize organic removal

- 10-20 percent increase in coagulant dose required
- **Predicted Increase in Organic Removal: 5-10%**

Lessons Learned

- Define a business use case at the beginning to frame the problem and guide the data analysis.
- Collaboration between subject matter experts and data scientists is key to understanding, analyzing, and modeling the data.
- SCADA data is generally easier to ingest for modeling; spreadsheet data can pose problems due to changes in formatting over time, hidden columns, and human error.

Copyright notice



Challenging today.
Reinventing tomorrow.