Self-Service Analytics and the Processing of Hydrocarbons

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Acknowledgements:

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IT Vizion, Inc.

Agenda

1. Self-service Analytics Introduction

2. Real world examples from Parkland Refining
    a. No Code
    b. Low Code
    c. Data Science Integration

3. Human factors and lessons learnt

Introduction

Business as usual = operational problems + (un)planned events + continuous improvement

...with all the plant data we have, why didn't we see it coming?

Using the right tool?

What to look for?

Timeliness

50k tag refinery generates 72 million data points every day

Example Refinery Engineer Analytics Use Cases

REFINERY A
CANADA

1) Predictive HEX fouling
2) HEX Network Pinch Point monitoring
3) Plant Steam Balance
4) Foaming Event Troubleshooting
5) DMC Monitoring / analytics
6) Multivariable controller KPI's analytics
7) FCC Compressor Anomaly Detection
8) HAZOP setpoint recommendations

REFINERY B
EUROPE

1) APS DMC Performance analysis across shift pattern – calculate Opportunity $/hr
2) ADU, determine minimum internal reflux necessary to achieve product Quality whilst maximising crude oil processing
3) LPG Mass balance for Unit
4) Real-time Unit Mass Balances
5) Furnace Status Energy Saving
6) HEX Fouling predictions
7) Column Optimal Operating targets
8) Let-down Valve degradation prediction

REFINERY C
INDIA

1) CDU overhead HEX failure prediction
2) CDU Best Efficiency Operation with integrated crude composition data
3) Steam Balancing across Unit
4) Boiler Efficiency Optimization for HP Steam Gen
5) Hydrogen consumption prediction to avoid flaring
6) Minimize PP losses to LPG
7) Maximise on-spec production of PP
8) Polymerisation in HEX prevention

Case Studies from the Burnaby Refinery

- No-Code Solutions
  - Conditional filtering of process data to identify anomalies
- Low-Code Solutions
  - Time series data cleaning and resampling
  - Identifying operating modes and estimating steady state gains
- Code Integration Solutions
  - APC controller constraint analytics
  - Scaling calculations using asset trees

The Analytics Value Pyramid

Figure adapted from Thusoo, Ashish. *Creating a Data-driven Enterprise with DataOps: Insights from Facebook, Uber, LinkedIn, Twitter, and EBay*. O'Reilly Media, 2017.

No-Code Solutions

Case study: Filtering process data by conditions (Compressor Troubleshooting)

Background

- Engineering team identified an incorrect low-flow trip SP on an air compressor. Recommended higher SP.
- However, Operations team raised concerns about 'blips' in the readings. Higher SP may cause spurious trips.
- Engineering team wanted to analyze historical process data to evaluate flow meter reliability

Case Study: Conditional Filtering of Process Data

Challenges and Initial Attempts

Objective: Identify time windows in the past 10 years when (1) the unit is running, but the (2) compressor flow dropped, to determine frequency and magnitude of flow measurement anomalies.

Conditions:

- Feed Rate ≥ 10 MBPD *(Blips are only valid when the unit is online)*
- Flow ≤ 1.2 MMSCFH

Challenges:

- Blips may only last several seconds
- Large 10-year dataset; pulling high-resolution data and doing calculations in Excel tedious and error prone.
- Initial analysis in Excel took engineering team several days to complete, without much confidence in the results

Case Study: Conditional Filtering of Process Data

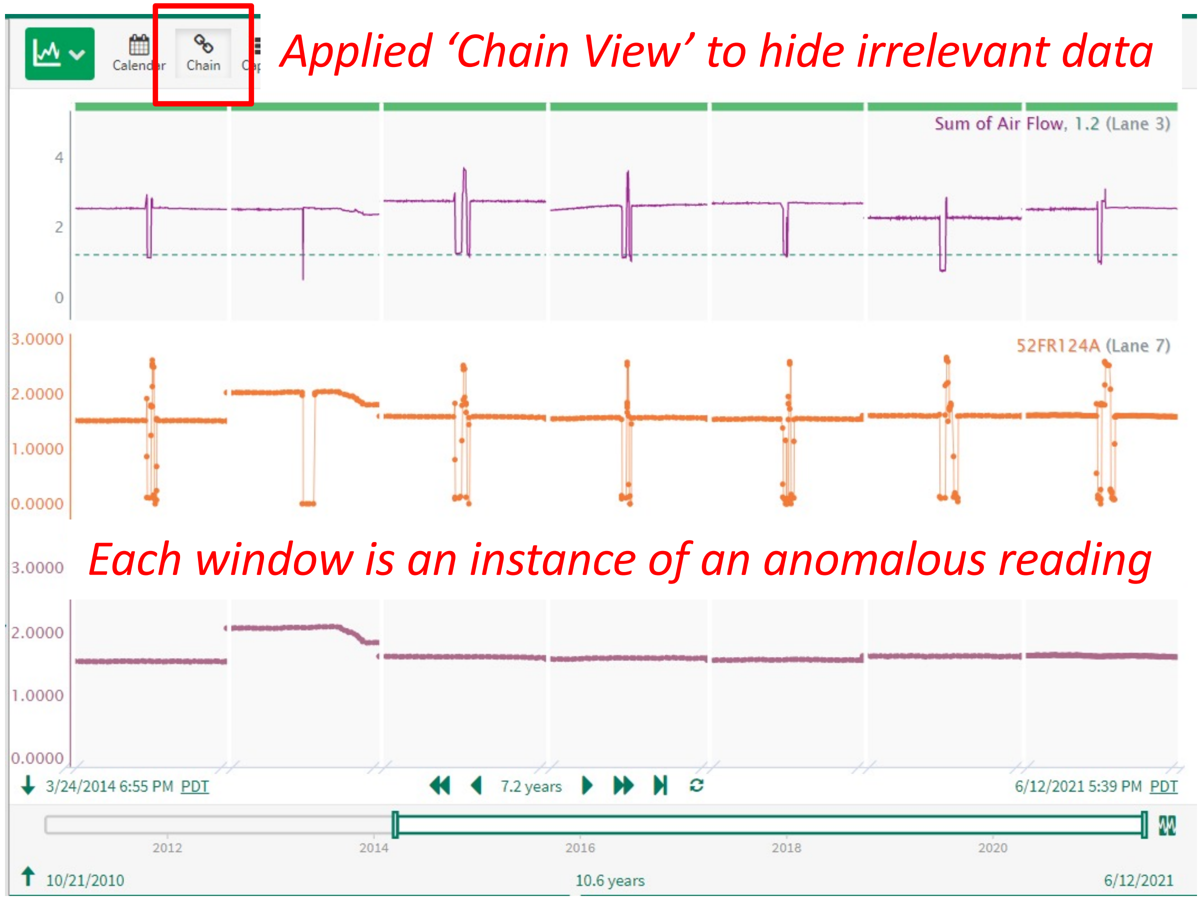
Composite Conditions and Capsules

Solution

- Used Seeq to filter data by conditions, creating *'capsules'* – slices of time that matches conditions defined
- Use 'Composite Conditions' to combine multiple conditions of interest and identify relevant time slices
- **Easy to setup in Seeq GUI.** Avoided tweaking historian retrieval settings and running IF-ELSE formulas in Excel over millions of rows.

Case Study: Conditional Filtering of Process Data

Results and Impact



Results

- Rapidly and correctly identified all time periods with anomalies in Seeq
- Redundant transmitters; transmitter 'A' has issues, 'B' functioning normally
- Confident that due to the existing 2oo2 trip voting logic, the new setpoints would have low risk of spurious trips.
  - Spurious trip and loss of production would cost ~$1mil per day of downtime
- Previous failed attempts in Excel took over 40 hours. Completed analysis correctly in Seeq in ~1 hour.

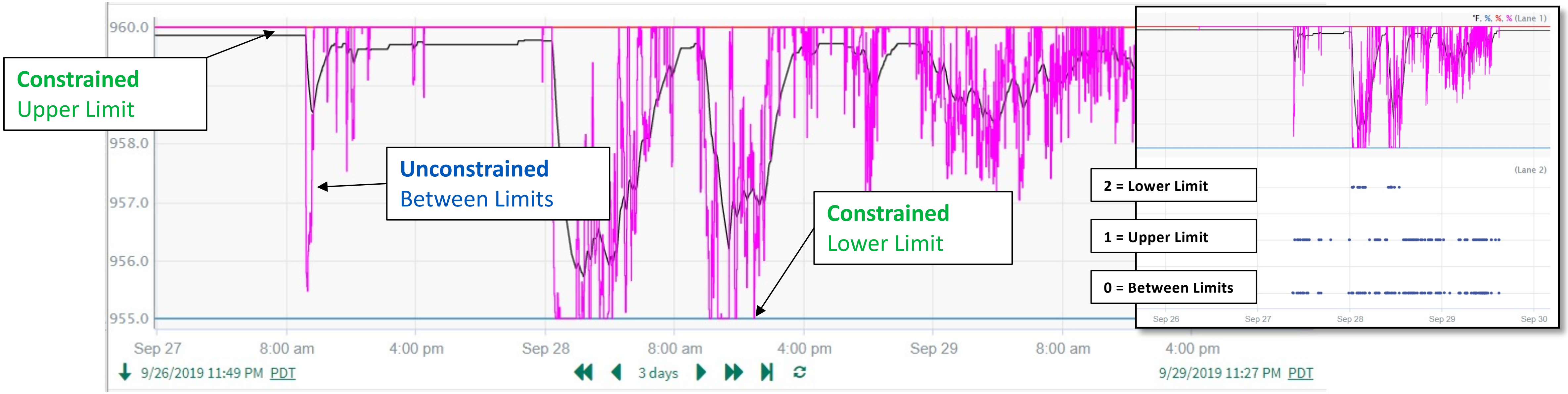
Low-Code Solutions

Case study: Time Series Data Wrangling & Resampling

Background

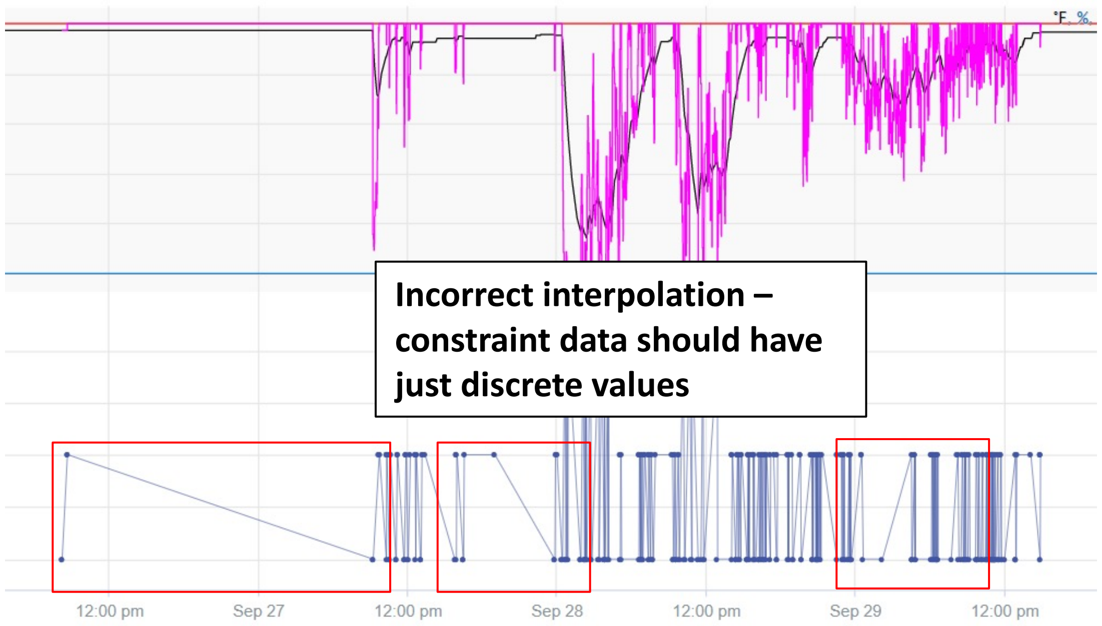
- Engineer wanted to analyze APC constraints (discrete, irregularly spaced time series data) for controller monitoring

- Difficult to perform calculations; wanted to resample into an evenly-spaced grid first



Case study: Time Series Data Wrangling & Resampling

Raw Data and Challenges



Objective

Calculate controller performance and KPIs using constraint data

Challenges

- Constraint data are irregularly spaced, large gaps when constraints are constant.
- Historian configured to collect data only when there is a value change.
- Data retrieval settings matter – may perform incorrect interpolation by default.

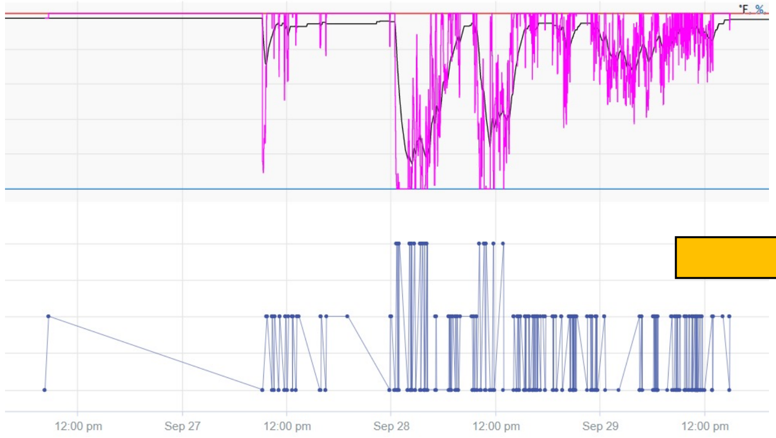
Case study: Time Series Data Wrangling & Resampling

Evenly-spaced grid with zero-order hold

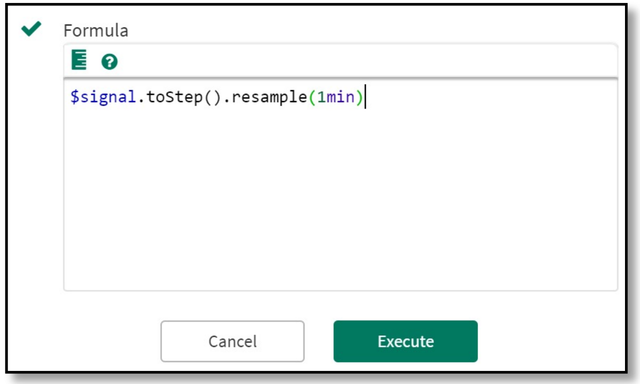
Solution

- First Excel attempt: pull raw data without interpolation, create rows with evenly-spaced timestamps, match raw data to timestamp with zero-order hold. Very time-consuming.

- Applied simple Seeq built-in formulas .**toStep()** for zero-order hold, and .**resample(1min)** to match controller execution cycle



Raw data



Seeq Formula

Cleaned, resampled data

Case study: Time Series Data Wrangling & Resampling

Results and Impact

Results

- Used Seeq as an effective data pre-processing tool: Easily and efficiently cleaned up messy raw data using low-code, native Seeq formulas
- Able to export cleaned data from Seeq into other tools like Python, Power BI or Spotfire for further manipulation, analysis or visualization
- *Next: Extension of APC constraint monitoring to multiple variables*

	A	B	C	D	E	F
1	Date-Time	FCC|RX|D1|52TAR1153|Measurement	FCC|RX|D1|52TAR1153|Operator_LL	FCC|RX|D1|52TAR1153|Operator_UL	FCC|RX|D1|52TAR1153|SS_Target	FCC|RX|D1|52TAR1153|Constraint
5556	2019-09-28T15:11:00	959.4561492	955	960	960	1
5557	2019-09-28T15:12:00	959.4712702	955	960	960	1
5558	2019-09-28T15:13:00	959.4866477	955	960	960	1
5559	2019-09-28T15:14:00			960	960	1
5560	2019-09-28T15:15:00			960	960	1
5561	2019-09-28T15:16:00			960	959.859375	0
5562	2019-09-28T15:17:00			960	959.90625	0
5563	2019-09-28T15:18:00	959.53125	955	960	959.90625	0
5564	2019-09-28T15:19:00	959.5337702	955	960	959.75	0
5565	2019-09-28T15:20:00	959.5489242	955	960	959.75	0
5566	2019-09-28T15:21:00	959.5605469	955	960	960	0
5567	2019-09-28T15:22:00	959.546875	955	960	958.453125	1
5568	2019-09-28T15:23:00	959.5335553	955	960	958.453125	1

Evenly-spaced timestamps at 1-minute interval

Low-Code Solutions

Case study: System identification

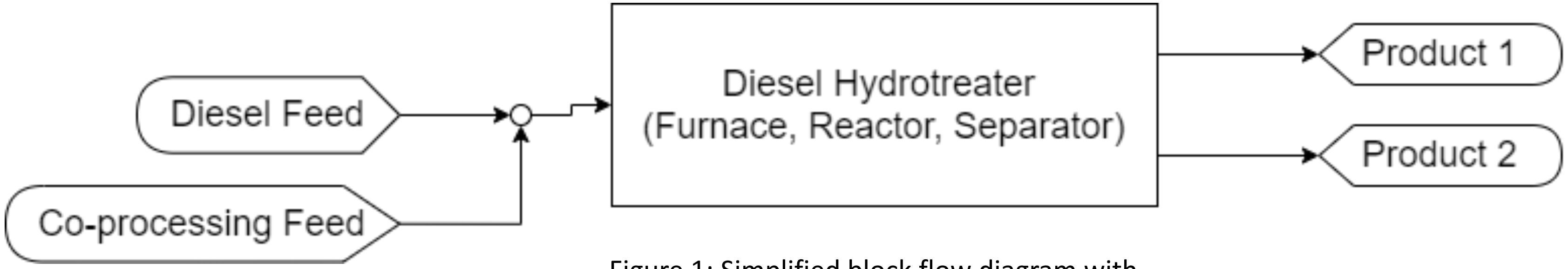


Figure 1: Simplified block flow diagram with Diesel Hydrotreater (DHT) feeds and products.

- Co-processing (co-pro) biofuel sources with crude strongly impacts Diesel Hydrotreater (DHT) performance and product specification
- Currently, reactor temperature is manually changed to account for feed
- It would be beneficial to add co-processing to the APC model, and we wanted to quickly estimate gains before running a full system identification
- **Goal:** to estimate co-processing gains using historical process data

System identification case study

Data cleaning and filtering

- Challenges: data can be inconsistent, messy, and exhibits large regions where it is not usable – such as <u>when the copro pipeline is unavailable</u>

Conditions to filter

Figure 2: Copro trend as a raw signal, with its smoothed signal, and with a final filtered signal shown over a 1-year period.

System identification case study

Isolating regions similar to step tests

- Regions resembling step tests can be identified by: cleaning copro data, calculating copro derivative, and isolating derivative spikes

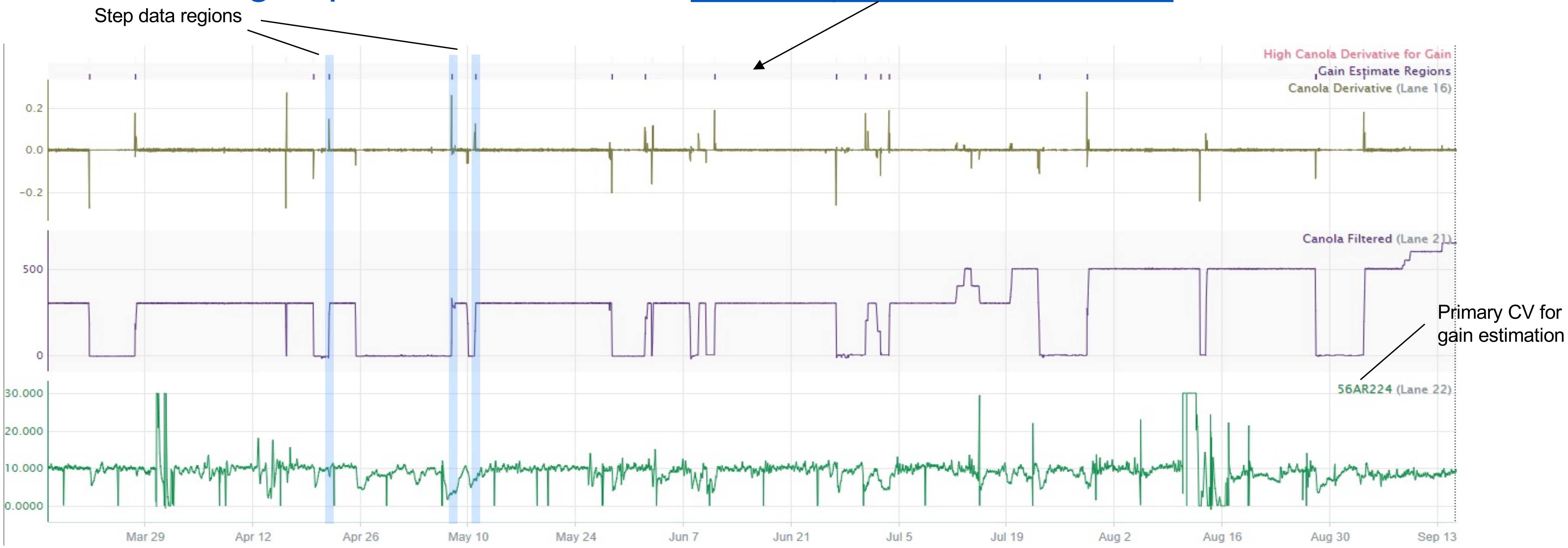


Figure 3: Filtered copro trend, copro derivative, and sulfur reading (the primary CV for gain estimation), showing possible analysis regions over a 6-month period.

System identification case study

Isolating regions similar to step tests – chain view

- Previously identified points with high derivative can be expanded to form capsules – in this case with a user-defined constant length

Capsules "chained" together using Seeq's built-in "Chain View"

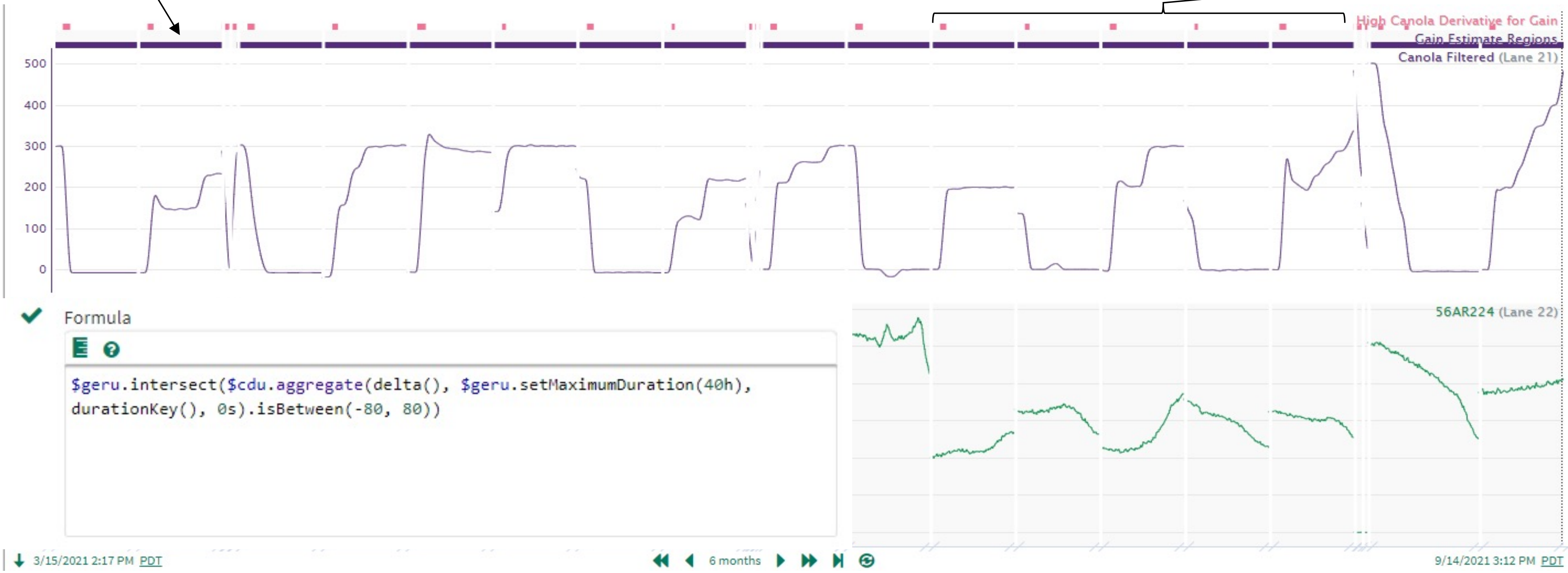


Figure 4: Seeq's "chain" view, which chains together capsules to make them adjacent. The regions isolated here are those relevant for calculating gain.

System identification case study

Gain estimation and compilation

- Capsules are combined to form conditions, allowing one calculation for gain to be applied over all relevant capsules in a single step

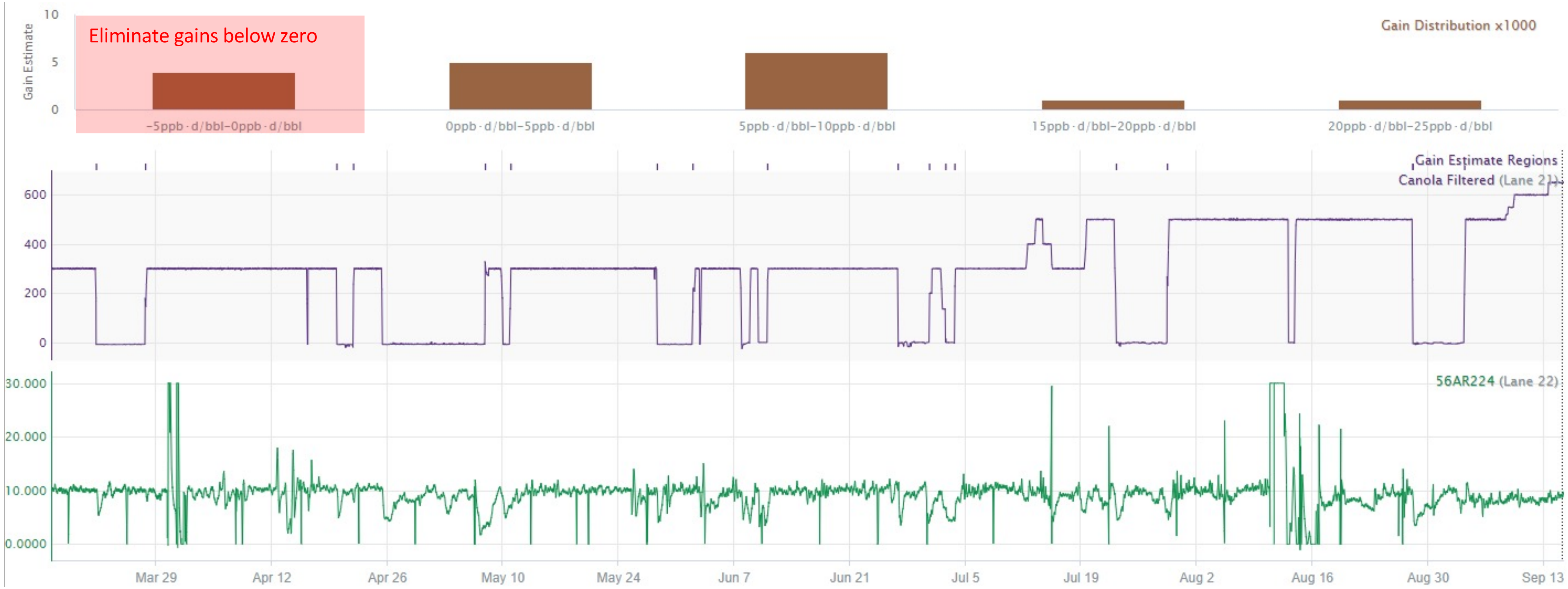


Figure 5: Trends for copro rate and sulfur reading, with a histogram showing the distribution of gains above. Gains are multiplied by 1000 for clarity.

System identification case study

Conclusions

- Average gain estimate is ~0.01 ppm / (bbl / d) – close to expectations
- Estimates are similar to results from the full system identification algorithm
- Seeq functionality allows for complex filtering/cleaning tasks and code-based calculations as well as interactive ad-hoc data visualization

Code Integration Solutions
Case study: APC constraint monitoring

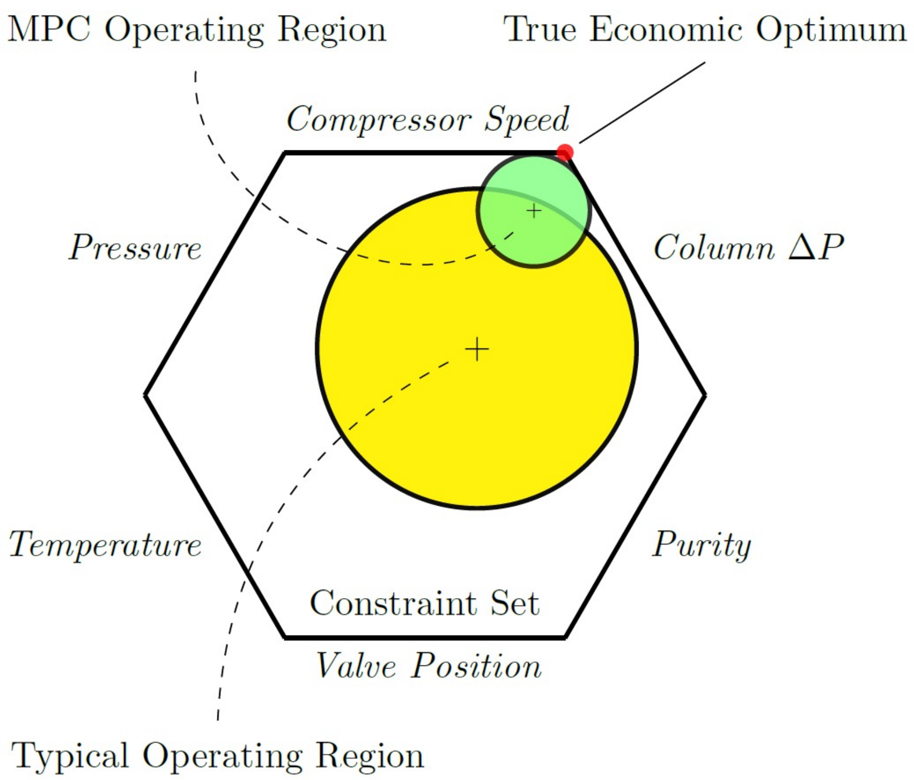
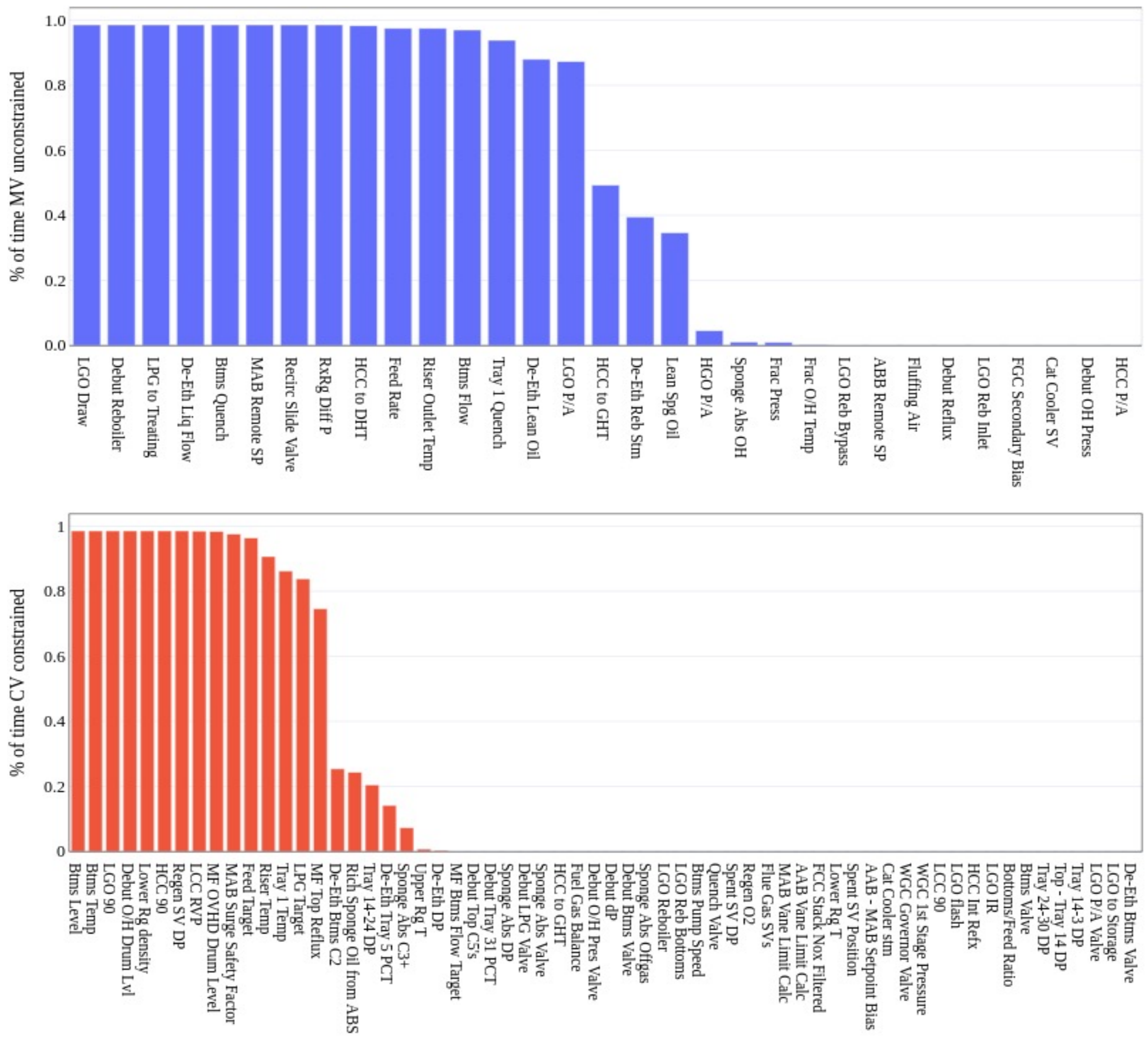


Figure 6: Stable operating region for a plant subject to constraints, represented by a 2-dimensional polygon. Each operating region's size is indicative of process variability during operation, and the vertices represent the boundaries of the feasible LP solution space as defined by variable limits. Figure adapted from Brooks (2017).

- APC systems involve both dynamic and steady-state (LP/QP) optimization
- LP solutions are dependent on variable constraints and cost configuration
- Conventional LP monitoring can be enhanced by focusing on constraints
- Constraints are monitored in Seeq Data Lab (SDL), integrated with PI historian

APC constraint monitoring case study

Percent Constraint Activity Plot (PCAP)



- Plot algorithms applied to PI data directly through SDL through Plotly
- PCAP gives an overview of variable constraints throughout time window
- Variables to note are those in between 0 and 100% (un)constrained

Figure 7: Percent Constraint Activity Plot (PCAP) developed by Kozub (2002), plotted using sample data from the FCC at the Burnaby refinery. For any time window, the top subplot is a chart sorted in descending order by the % of time each MV is unconstrained. These MVs are not part the LP optimizer solution. The inverse is true for CVs – the bottom subplot shows the % of time a CV is constrained.

APC constraint monitoring case study

Dynamic Constraint Activity Trends (DCAT)

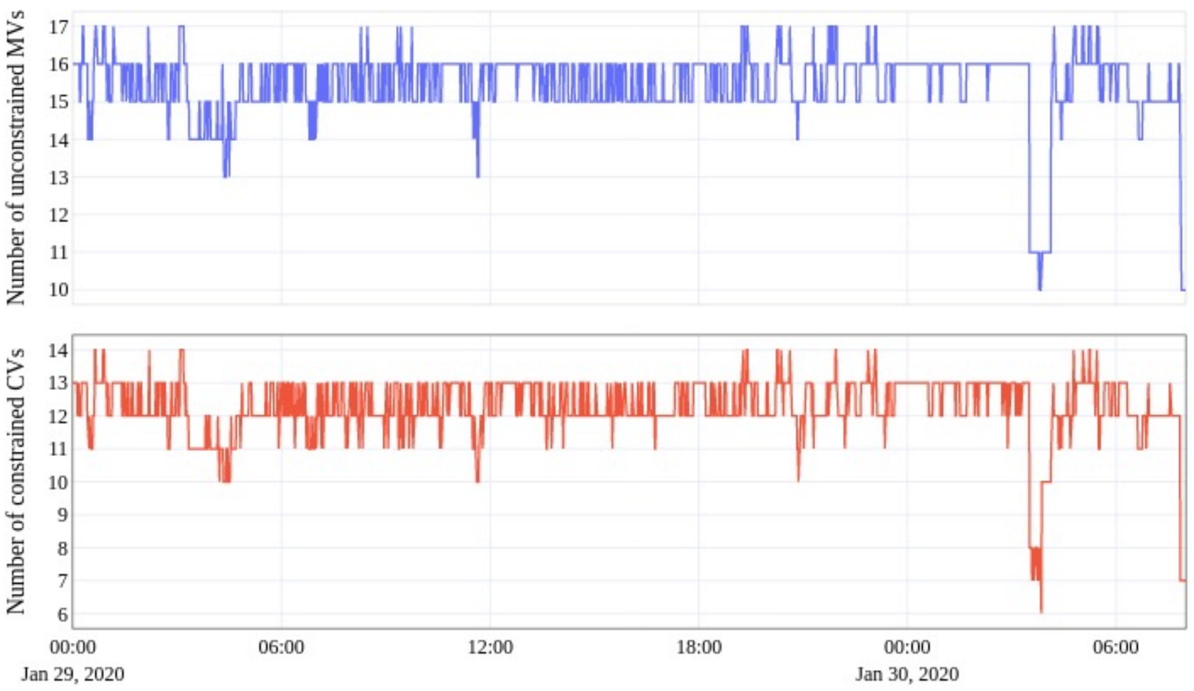


Figure 8: Dynamic Constraint Activity Trends (DCAT) developed by Kozub (2002), plotting using sample data from the FCC at the Burnaby refinery. The two subplots provide an overview of variable constraint statuses in the time domain. At any given time, the subplot shows the number of MVs available for control (i.e. unconstrained) and CVs that are controlled at limits (i.e. constrained). A sudden drop in the number of unconstrained MVs is indicative of potential controller faults that may need further investigation.

- Plot algorithms applied to PI data directly through SDL through Plotly
- DCAT shows variable constraints over time, showing regions of instability
- Frequent DCAT chattering can indicate LP instability
- Variable constraints monitored individually to identify root causes

PARKLAND

APC constraint monitoring case study

Asset tree scaling

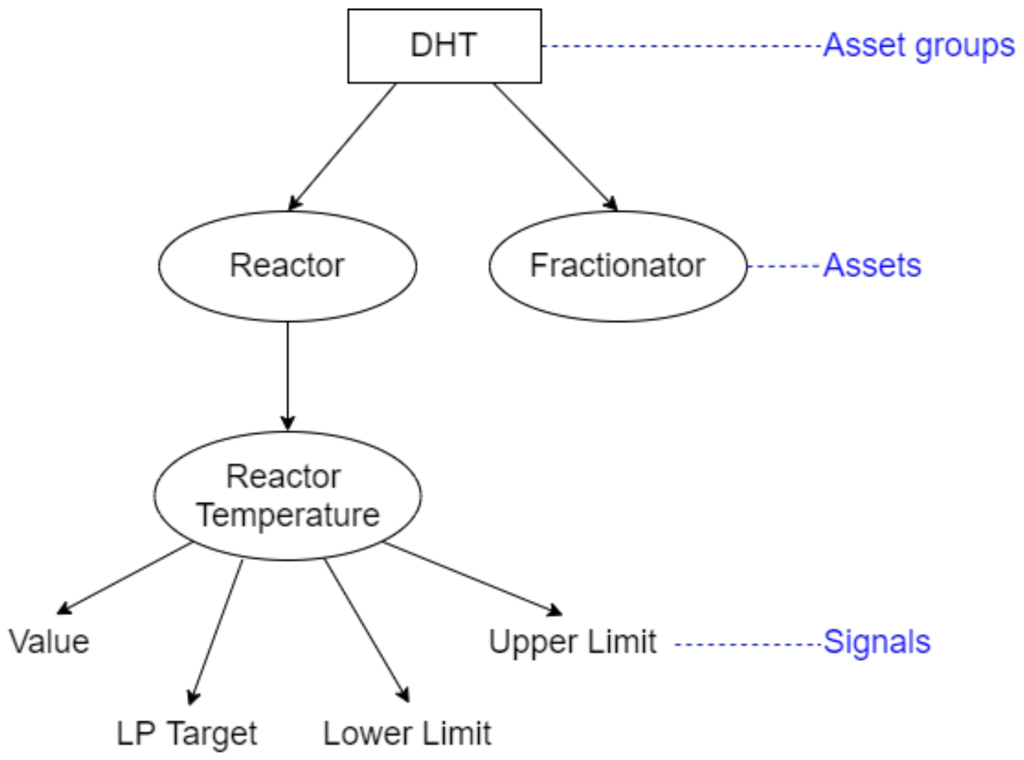


Figure 9: Sample asset tree structure in the DHT at the Burnaby refinery. Going up in terms of abstraction, signals (and conditions/capsules) can be grouped together to form assets. These assets can be grouped together under other assets or placed into a containing asset group. The tree structure tells users how their signals will fit into the larger context of their data, making navigation through trends easier.

- We can improve this analysis by implementing it across controllers
- SDL solutions can be scaled using the `seeq.spy.assets` library
- Defining an asset tree structure is easily rolled out to other controllers
- Asset trees can also be configured in Seeq GUI (new feature)

APC constraint monitoring
Conclusions

- Constraint analysis as performed by Kozub (2002) simplifies the analysis of process faults by highlighting regions with LP instability
- Basic SDL functionality is like other code tools, but SDL integration with PI and interactive data viz greatly facilitates LP analysis
- Seeq asset structure allows users to automate these analyses such that their implementation can be scaled up extremely easily

Lessons Learnt

1. Tacit knowledge is key

- Cleansing Data
- Training data set periods
- Tuning logic for good input data
- Tuning logic for anomaly state
- Corresponding Events

2. Anomaly Detection is just a start

- Troubleshoot the anomaly
- Scenario test options to resolve
- Validate fix / return to expected

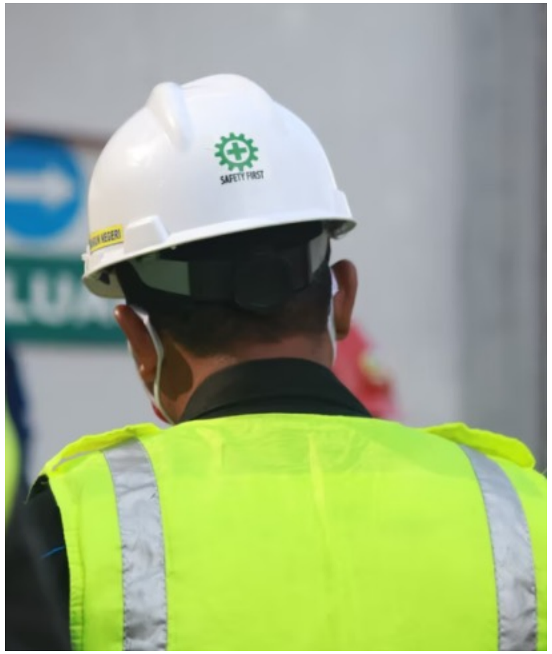
3. Your data is analytics ready

- You don’t have to boil the ocean (Data Monolith Delays)
- No need to code from scratch
- Apply No-code / low-code data cleansing
- New Soft sensors
- Uncover errors in legacy analysis

Lessons Learnt

4. Prepare the workforce

- Start with a test drive
- Identify Internal champions
- Give them time to learn
- Tool experts on-hand
- Flexible training options



Summary

Self service analytics is,

- Easy to Use, Easy to Learn, Shareable and robust
- Completed quickly with timely access and timely results
- Able to provide new kinds of analysis
- Capable of handling years worth of time series data from disparate sources
- Easy to Maintain, with hosting and SaaS options
- Delivering better operational and business outcomes

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