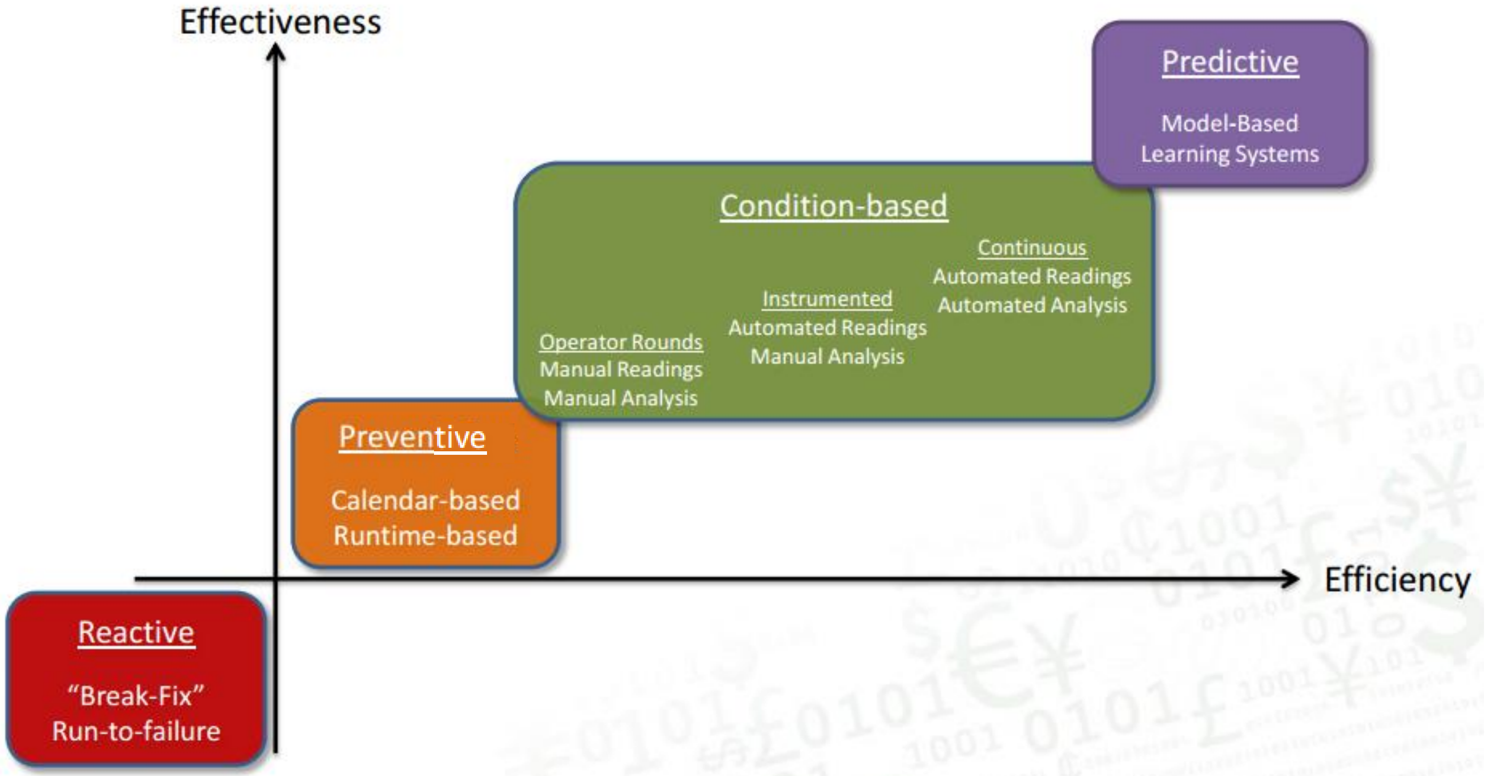
Condition Based Maintenance with PI AF

Keith Pierce and Curt Hertler, OSIsoft

2016 T & D Users Group

OSIsoft®

Moving Away from Calendar-based Maintenance



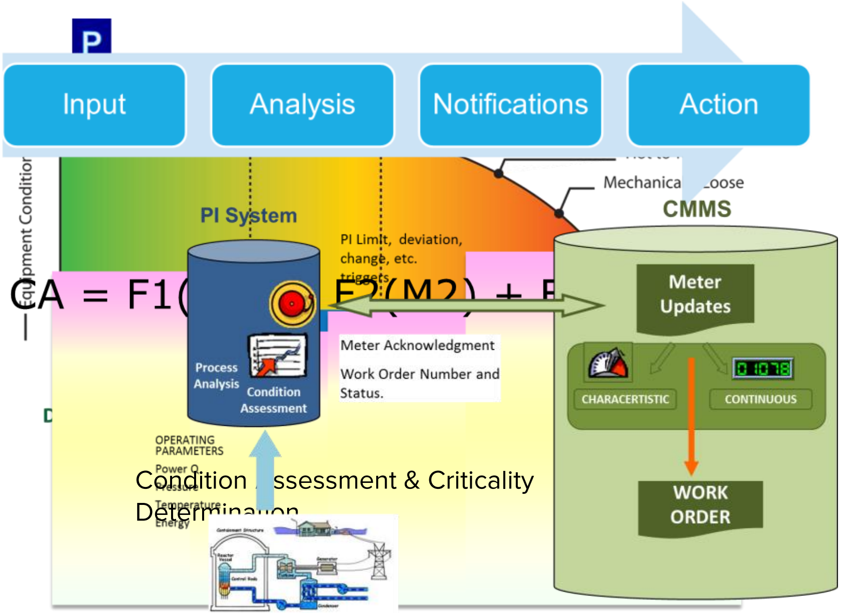
CBM means different things to different people

Incipient Failure Detection

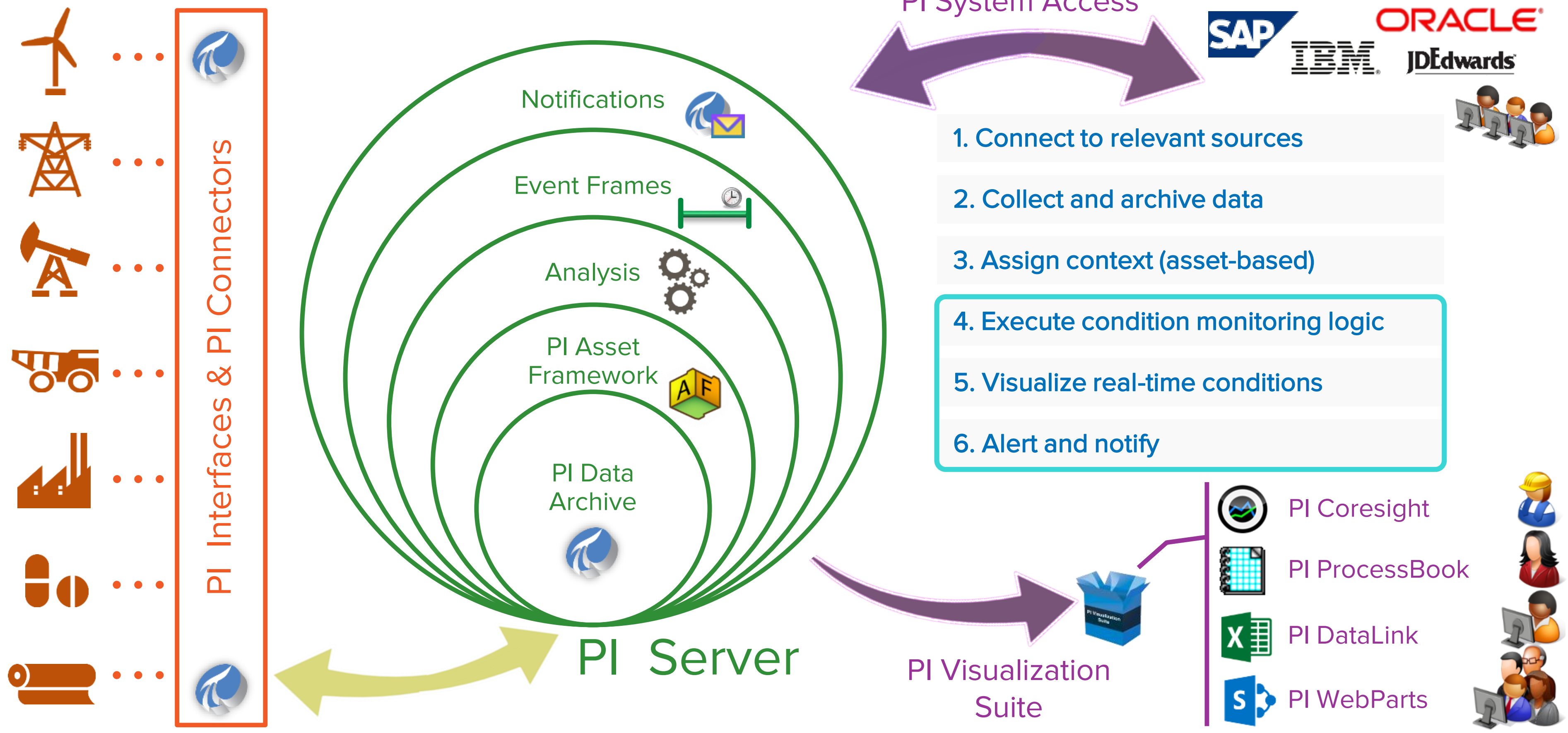
Condition Monitoring

Condition Assessment

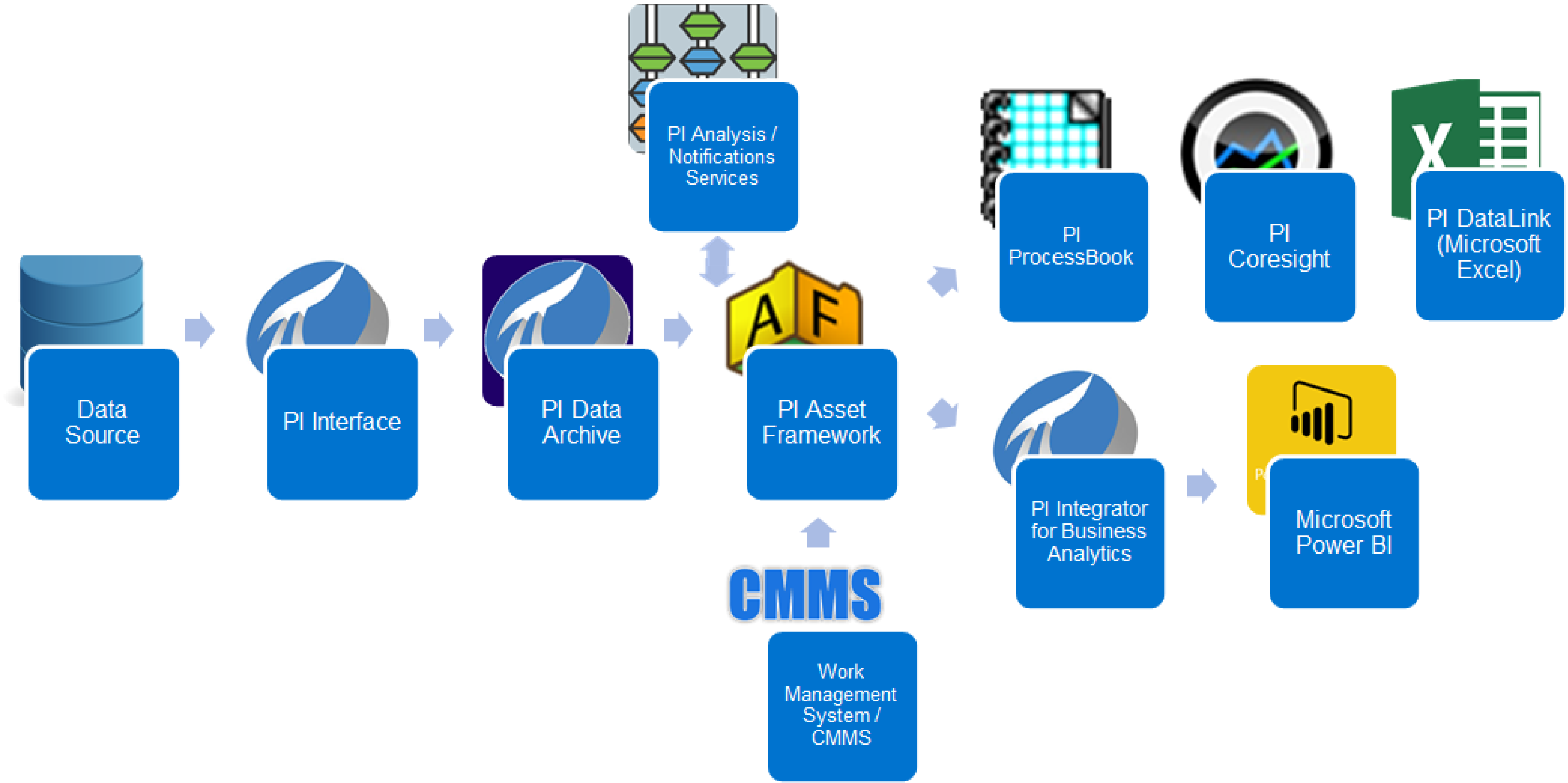
CBM Preventive Maintenance



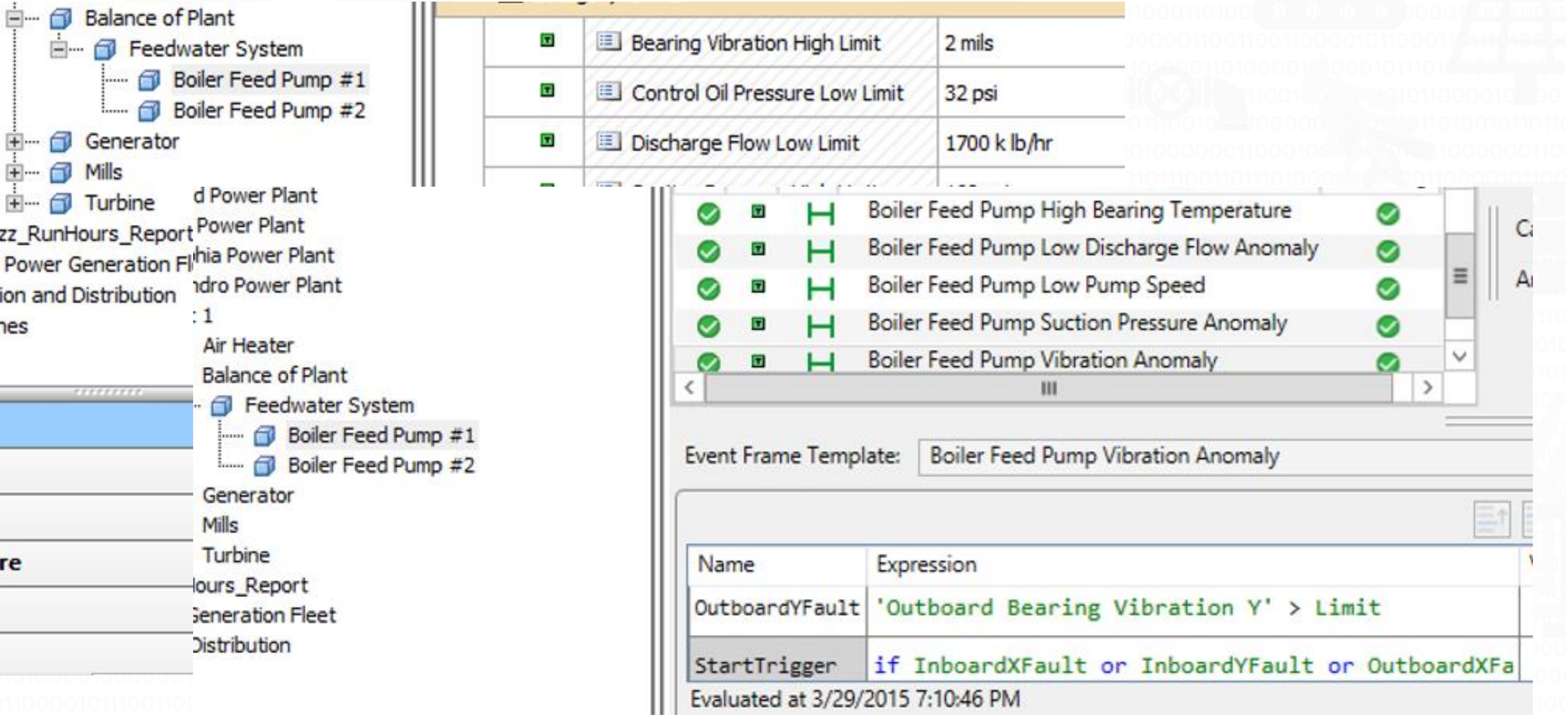
The 6 Steps of CBM with the PI System



Data Flow and PI System Tools



Condition Monitoring with PI



Notify asset owner – include links to displays

From: DoNotReply@OSIsoft_PINotif.com [mailto:DoNotReply@OSIsoft_PINotif.com]
Sent: Thursday, September 25, 2014 7:00 AM
To: [redacted]
Subject: Production KPIs] generated a new notification event.

Name: Daily Production KPIs

Trigger Time: 9/25/2014 6:00:00 AM Central Daylight Time (GMT-05:00:00)
Unit: Batch Operation

In the Last 24 hours:

Cycles = 259 count

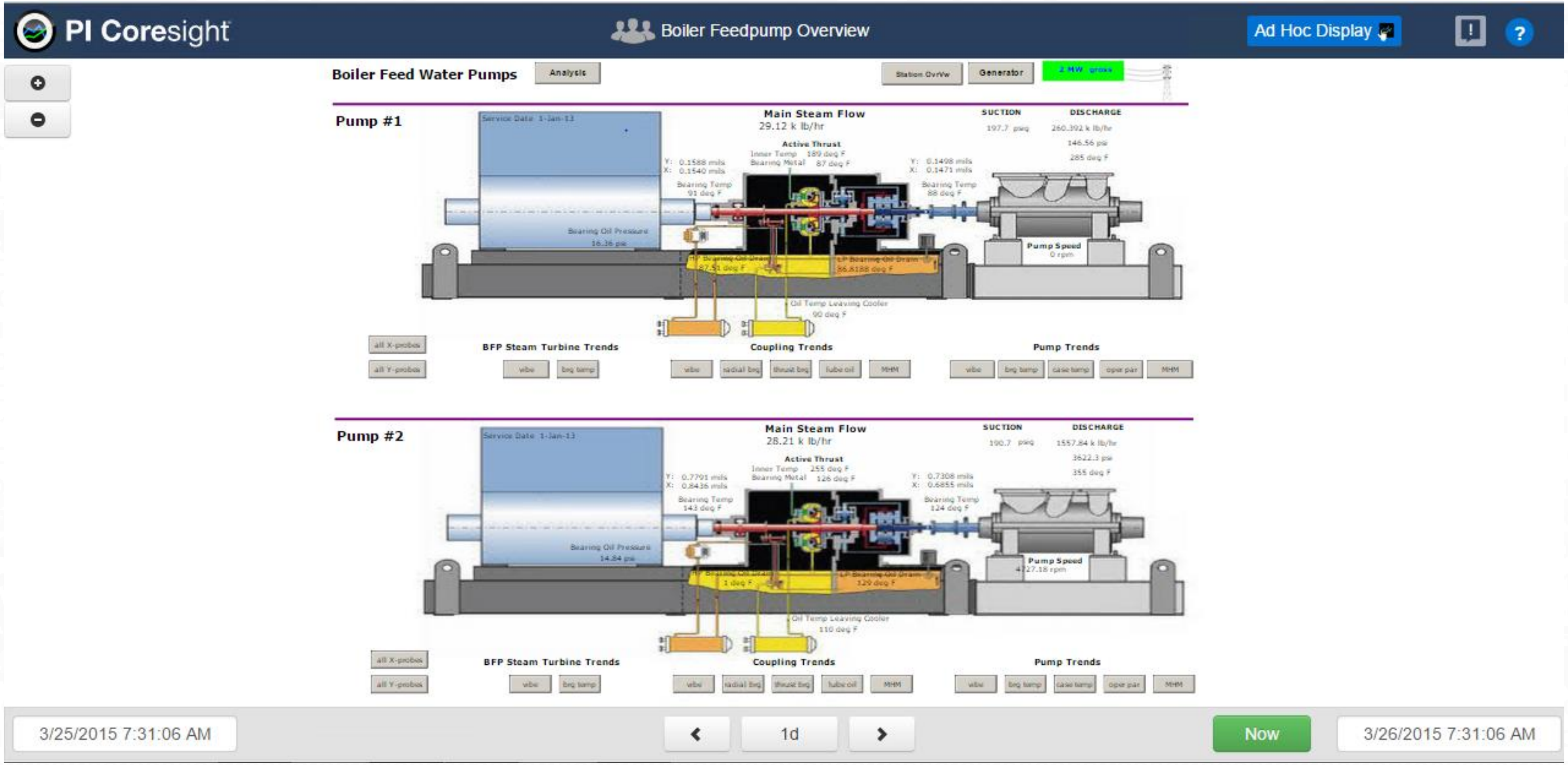
Downtime = 2.583333 h

Feed 1 = 43062.45 US gal

Feed 2 = 20236.69 US gal

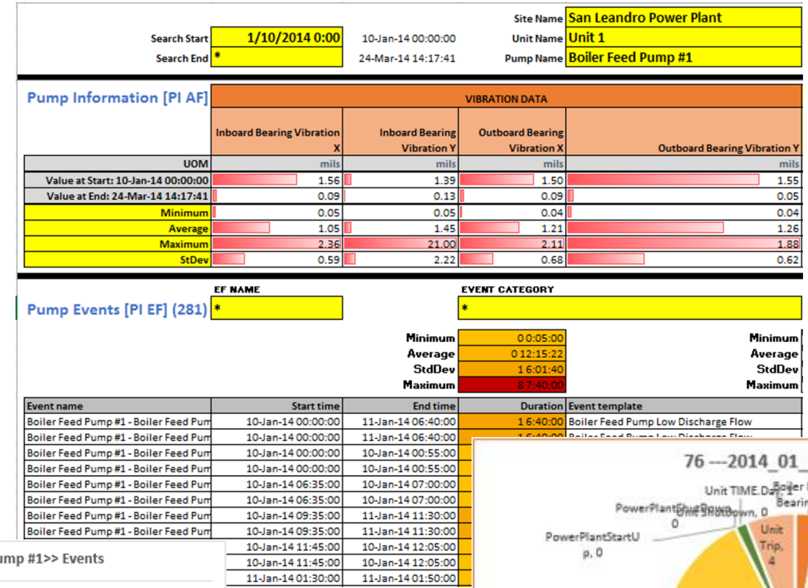
http://dfpicoresight/Coresight/#/PBDisplays/10073

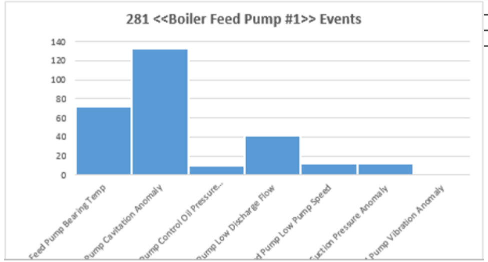
Linked PI System display from Notifications

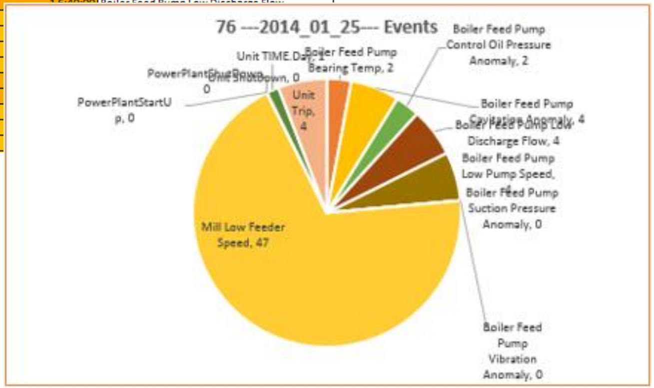


PI Asset Analytics can be used to create Event Frames

- Event Frames
- Analyze Events over time
- Find common cause/failure modes
- Report on efficiency



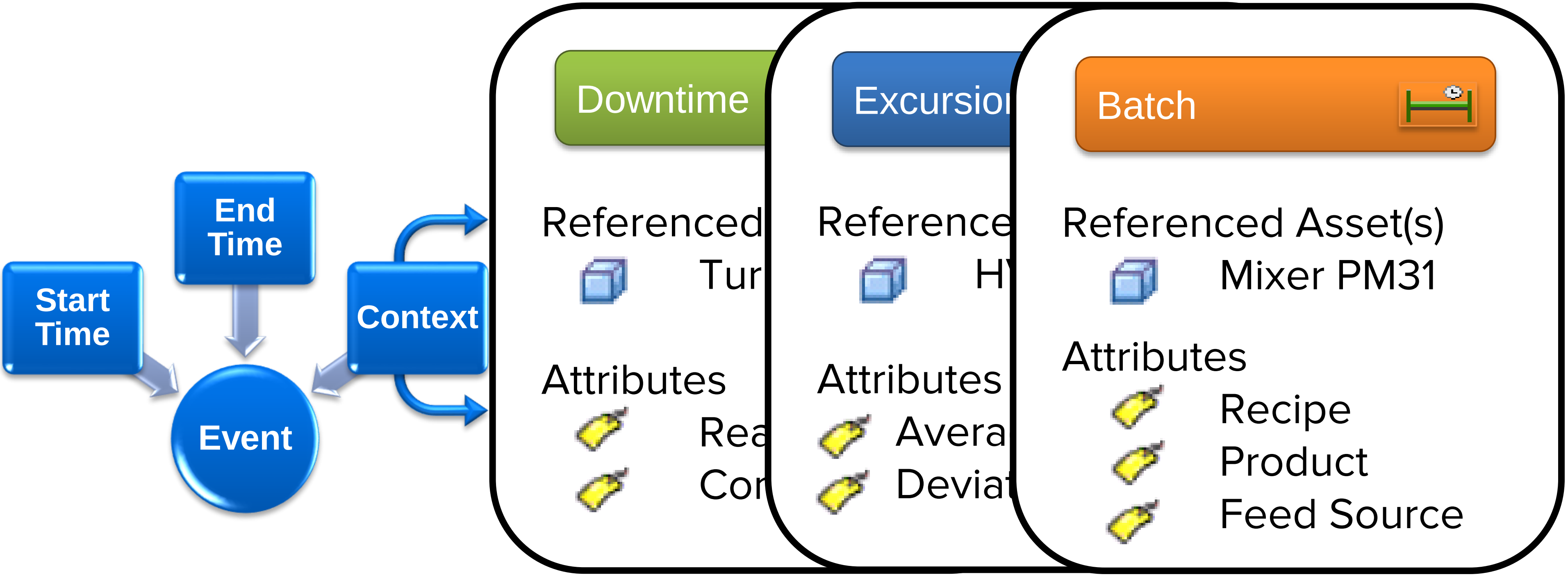




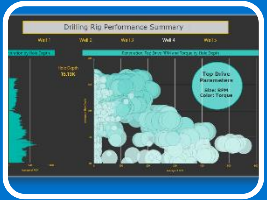
Framing data - Start/End of a time window…

Define your Events

PI EF (Microsoft SQL)

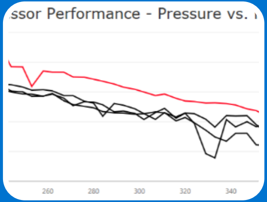


Analytics Outcomes



Insights

- Operational Insight
- Unsuspected or Validated Correlation
- Multivariate analysis



Monitoring

- Limit, Rate of Change
- Efficiency, Performance, Accumulation
- Pattern Recognition

Use PI (time-series) data within IT

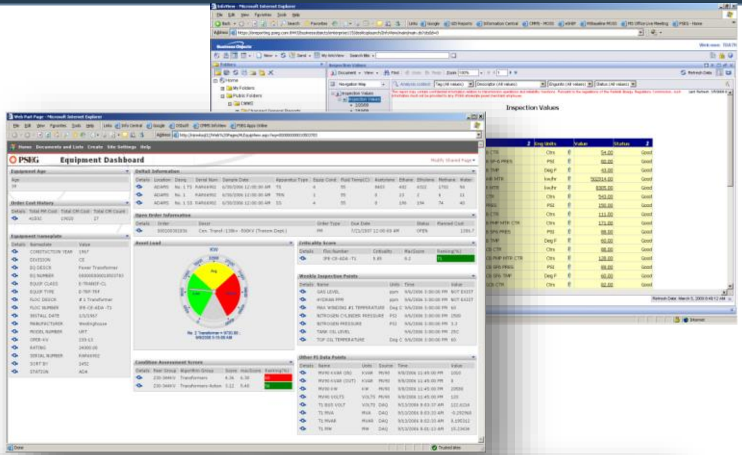
- Variety of data correlation
- Transform Business Process
- KPI Reporting (BI)

PSE&G: Condition Based Maintenance and Asset Management

POWER & UTILITIES

“We get a detailed breakdown on equipment costs and man/hours to service that gives us important business benefits. Without the use of the PI System, it would have taken us several months to gather and analyze the information.”

Angela Rothweiler, Principal Engin



Customer Business Challenge

- Providing the highest reliability Power Distribution is requirement
- Minimize Maintenance Costs

Solution

- Implemented automatic data collection and notifications to SAP PM
- Set up standard business rules for condition based maintenance using the PI System Analytics
- Provided focused view into equipment
- Provided Financial access to data by Business Objects query

Customer Results / Benefits

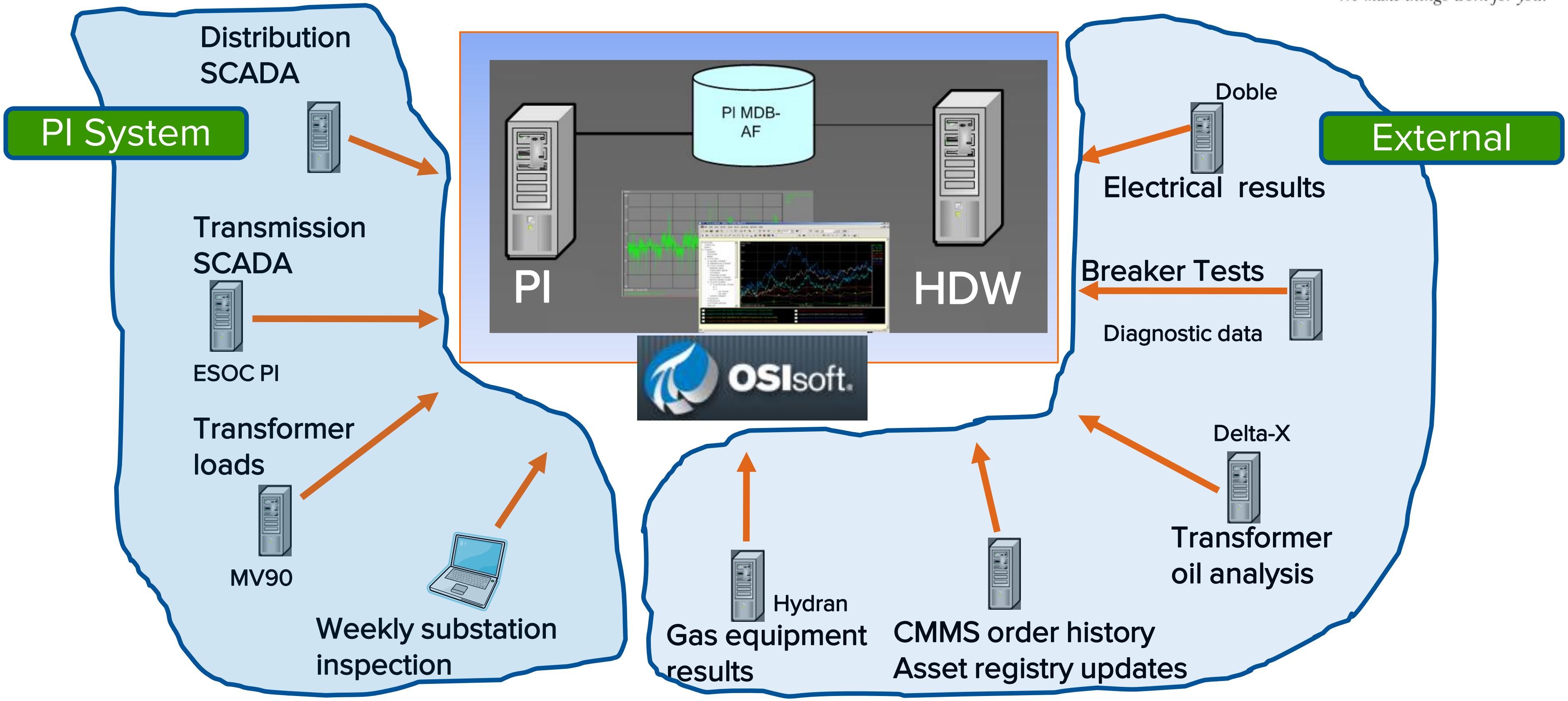
- Holds Reliability award for Mid Atlantic States for last 7 years
- Named most reliable Power Company in America
- Focused maintenance expenditures on needed targets

Calculation Approach

- Calculation Structure
  - CA = F1(M1) + F2(M2) + F3(M3) + …
  - Factors driven by data available
  - Example Factors
    - CM Cost & Count for Past 6 Months
    - Operation Count for Past 6/12 Months
    - Gas Analysis – Change over time
    - Average Load over Time
- Peer Groups
  - Apply calculations by peer group
  - Voltage, Class, Type
  - Example Groups:
    - 26KV – 69KV GCB
    - 138KV+ Power Transformer
    - LTC Vacuum Tanks

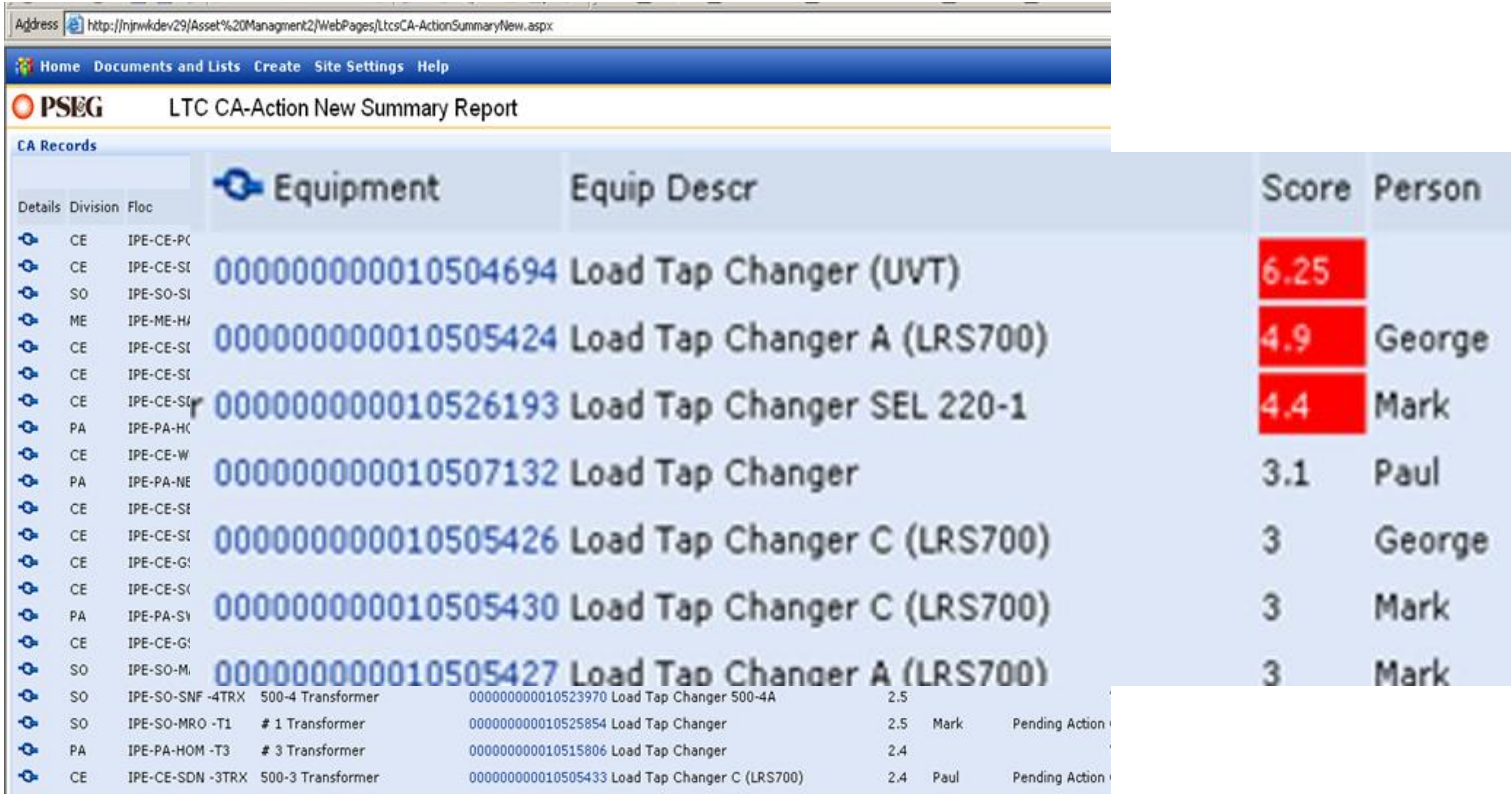
CBM data sources (T&D example)

PSEG
We make things work for you.



Asset health score

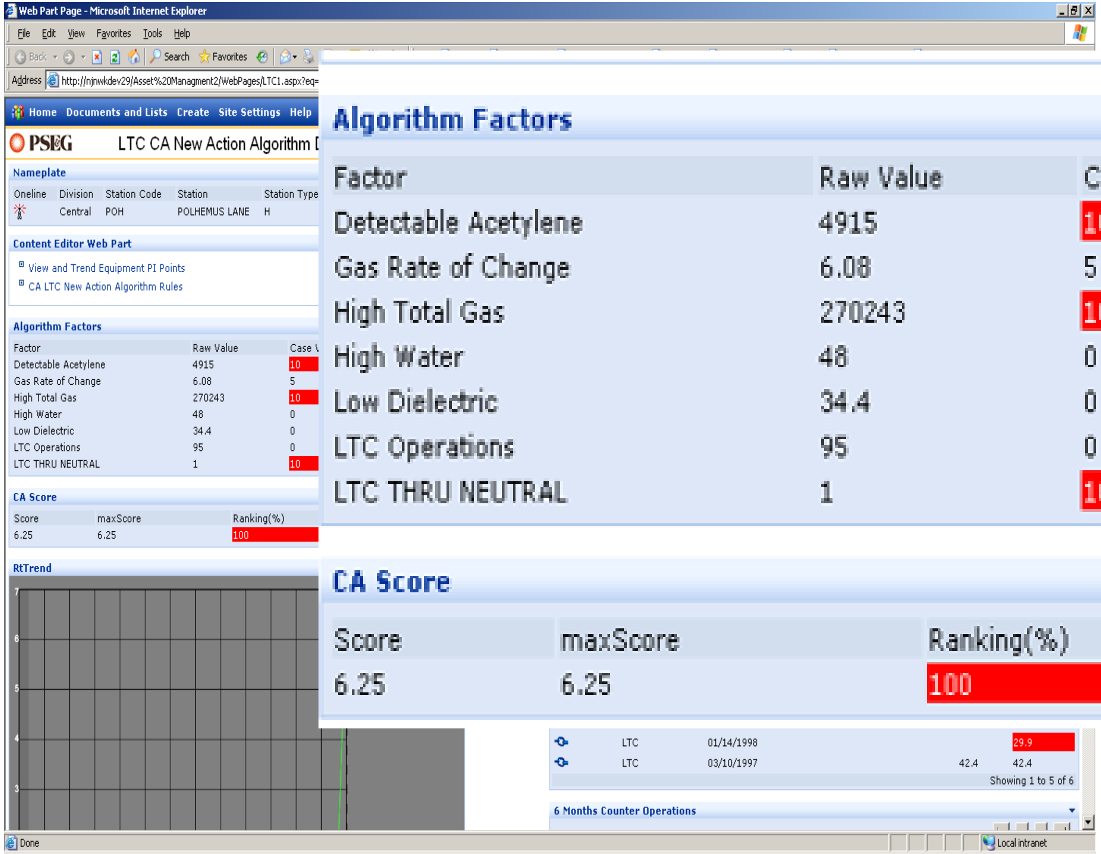
PSEG
We make things work for you.



http://videostar.osisoft.com/Regional_Seminars/2009/Boston/Video/RS2009_Boston_CBM_PSEG_Gopal_Rothweiler.wmv

Asset health score - details

PSEG
We make things work for you.



Algorithm Factors

Factor	Raw Value	Case Value	Weight %	Score
Detectable Acetylene	4915	10	25	2.5
Gas Rate of Change	6.08	5	15	0.75
High Total Gas	270243	10	20	2
High Water	48	0	10	0
Low Dielectric	34.4	0	10	0
LTC Operations	95	0	10	0
LTC THRU NEUTRAL	1	10	10	1

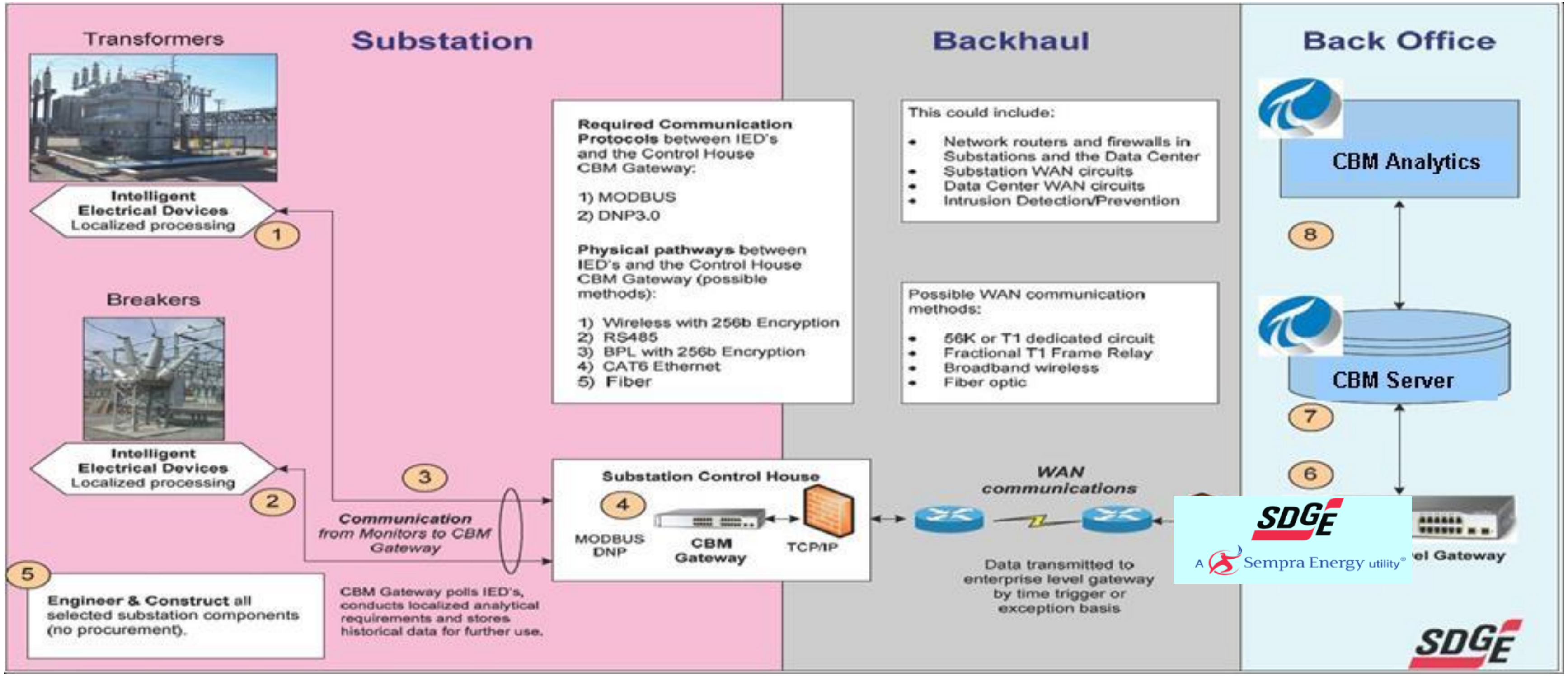
CA Score

Score	maxScore	Ranking(%)	Peer Group
6.25	6.25	100	VACUUM

Benefits Summary

- More targeted capital expenditures with eventual overall reductions
- As incipient failures are reduced, corrective maintenance costs go down
- With a move to condition-based maintenance, calendar-based preventive maintenance is reduced
- Automation of condition-based notifications (emails, pages, maintenance notifications, etc.)
- Codification of organizational intelligence into condition-based algorithms
- Prioritization of maintenance, shorter downtimes, do the right work at the right time
- Improved visualization of asset health status
- Improved decision making capabilities

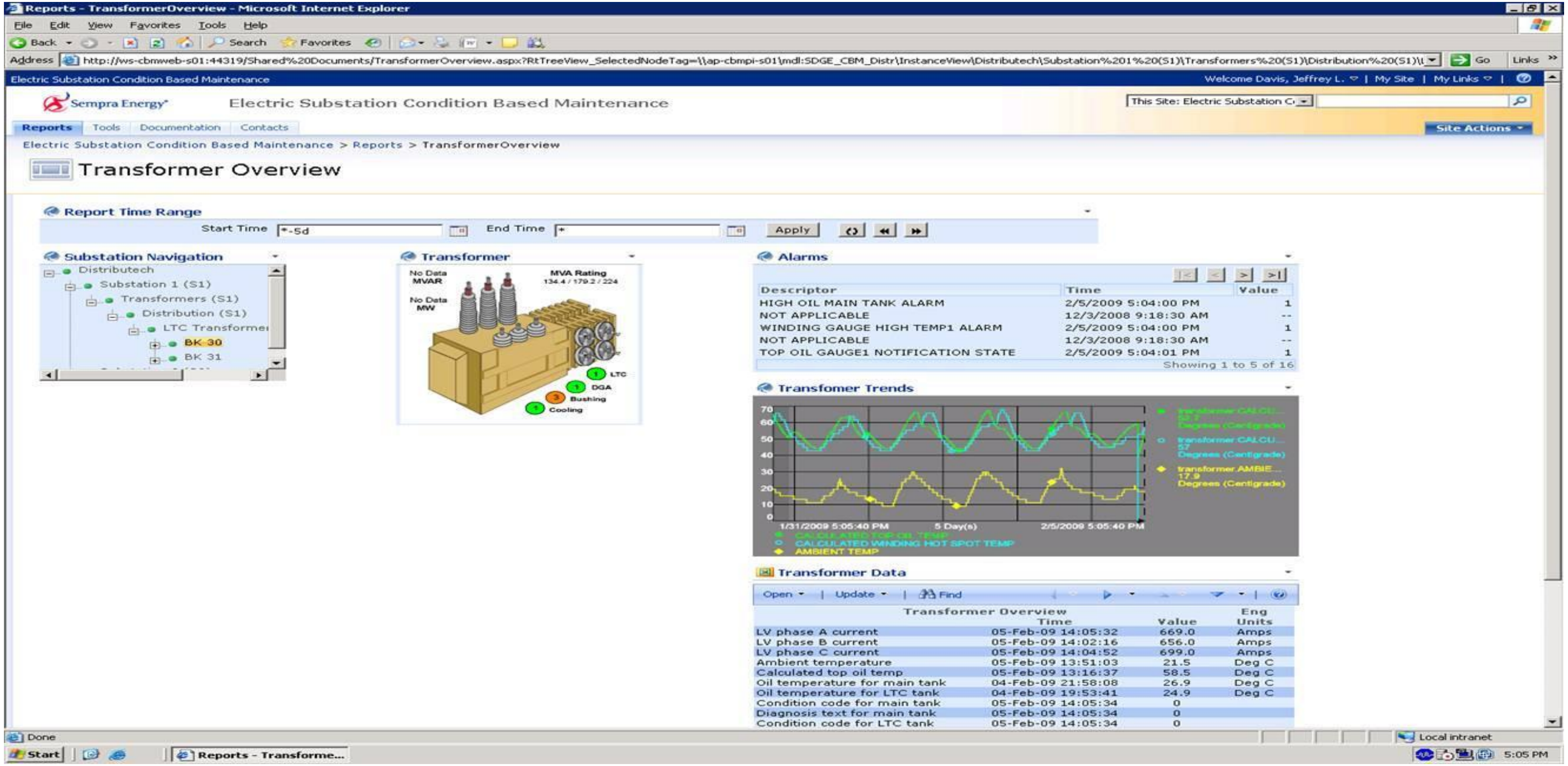
SDG&E Technical Overview



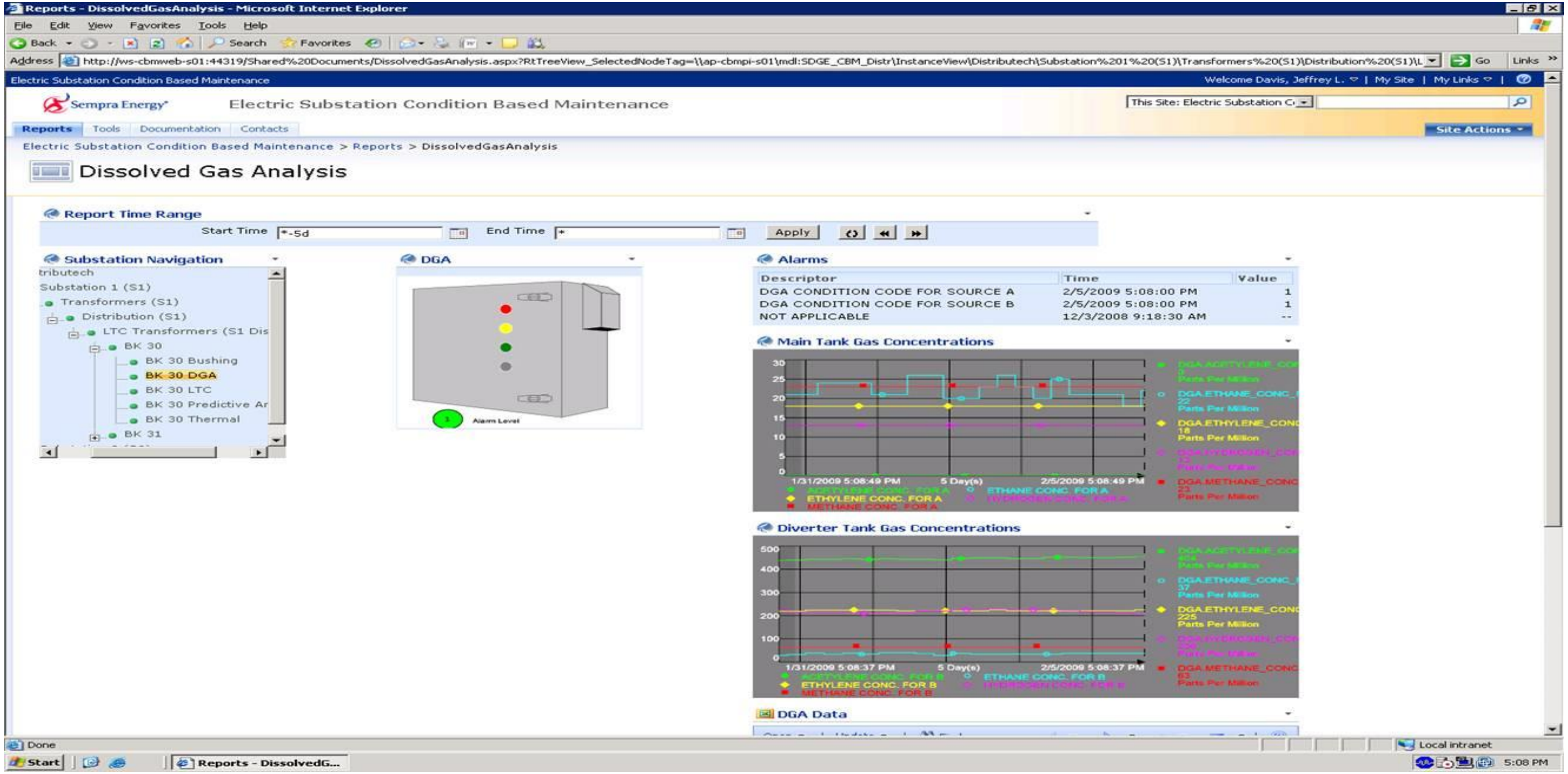
Condition Monitoring Examples

- Transformer
  - Detect Loss of Cooling Fans/Pumps
  - Detect Failed Control Contactor for Cooling Fans/Pumps
  - Collect Data on Run Hours for Fans/Pumps
  - Oil Temperature (Top & Bottom)
  - Winding Hot Spot Temperature (Calculated)
  - LV Load Current
  - Ambient Temperature
  - Eight gas DGA
  - Cooling System Manager / Monitor
  - HV Bushing Power Factor
  - LV Bushing Power Factor
  - LTC Position Indication & Operations Counter
  - LTC Motor Energy
  - Conservator Integrity
  - Provide Break-Out of Miscellaneous Bank Alarms
- Breakers
  - Gas Pressure / Density
  - Ambient Temperature
  - Air Compressor / Hydraulic Motor Hour Meter (optional-not in use)

PI Visualization



PI Visualization



OSIsoft Partner Ecosphere

Partner Types

OSIsoft. SYSTEM INTEGRATOR PARTNER

System Integrator

System Integrator's (SI's) are partners who provide a variety of services, such as implementation and integration, strategic consulting, configuration, application

OSIsoft. APPLICATION PARTNER

Application

Application partners or Independent Software Vendors are partners that provide their own software applications and products which integrate and extend the PI System to provide additional functionality for customers.

OSIsoft. TECHNOLOGY PARTNER

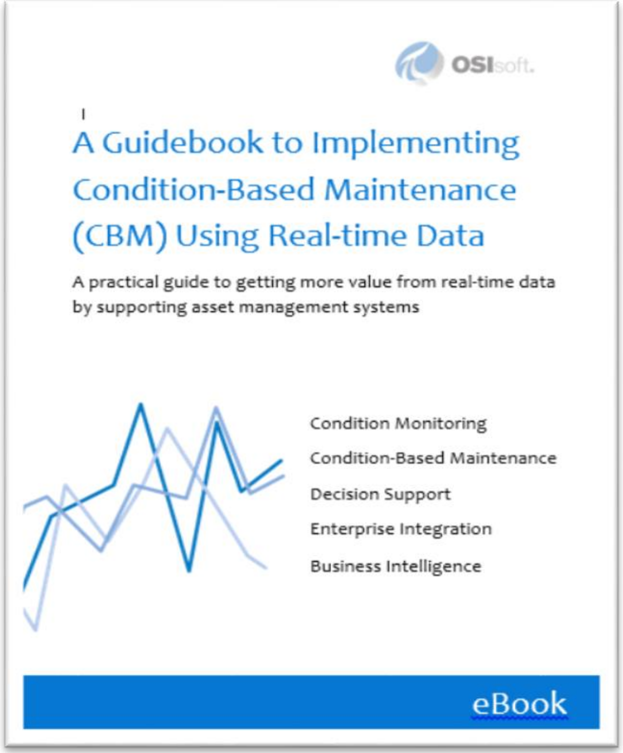
Technology

Technology partners provide products and services with demonstrated interoperability with OSIsoft's technologies and demonstrated relevance to OSIsoft's customers.

Roadmap to Readiness Resources

- www.osisoft.com/corporate/business-analytics
- https://techsupport.osisoft.com/Products/Product-Roadmap
- http://pages.osisoft.com/Business-Analytics.html
- Learning channel, techcon, AF Example Kits, SPOC, etc.

CBM Prescriptive Guidance



Link: http://pages.osisoft.com/rs/osisoftllc/images/CBM%20Guidebook.pdf

Terms & Definitions

Implementation Guidance

PI System Overview for CBM

PI System Integration w/ CMMS

Enabling Opportunities

Solution Examples

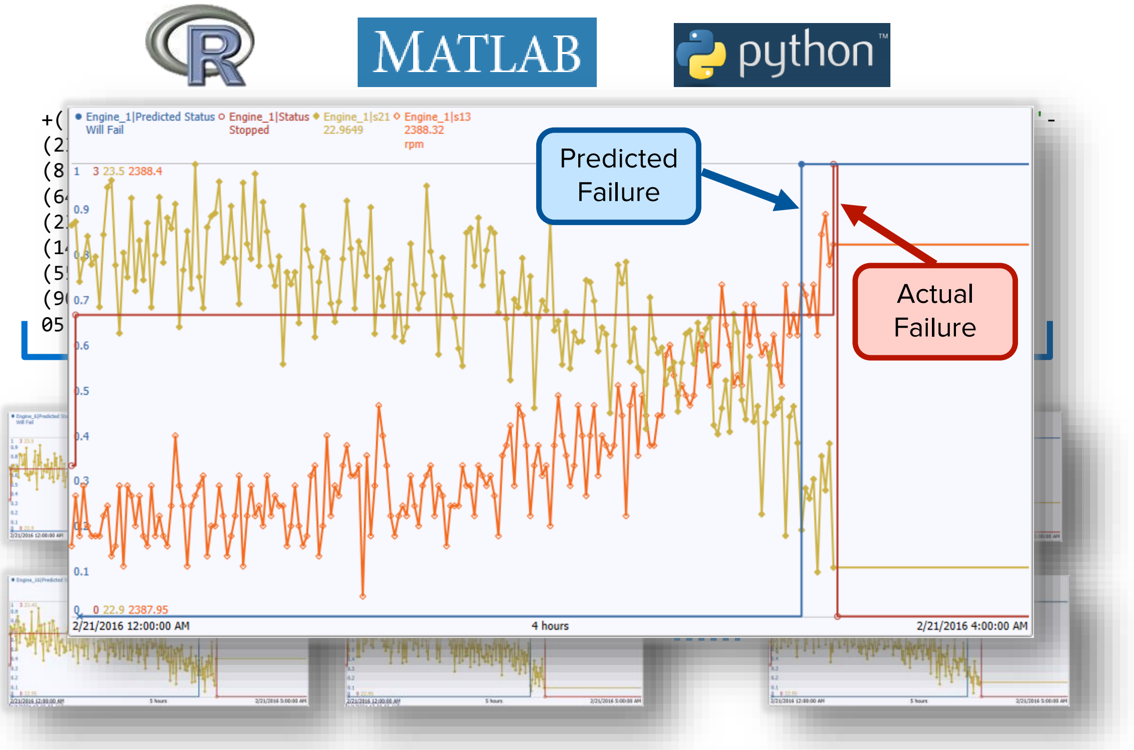
Industry References

Predictive Analytics

Statistical Modelling - *Predict Asset Failure*

Complex systems; descriptive equations are too numerous and interrelated.

- Create an operationalized model to reduce unplanned downtime for 100 engines.
- Extract data for 2,300 sensors leading up to engine failures.
- Developed a statistical model using R for predicting failure.
- Tested and operationalized for all engines against historical data.



All Engines

Predictive Modelling Process - Example

Using data taken from 100 engine failures, develop and operationalize a model for predicting failure to avoid unplanned downtime in real time.

Step 1 - Use AF Analytics to create Event Frames for engine operating periods.

Step 2 - Publish a text file “Event View” dataset from the PI AF using the PI Integrator for Business Analytics (BA).

Step 3 - Use the functionality of R to analyze this dataset and to develop a qualified predictive model for determining remaining useful life (RUL).

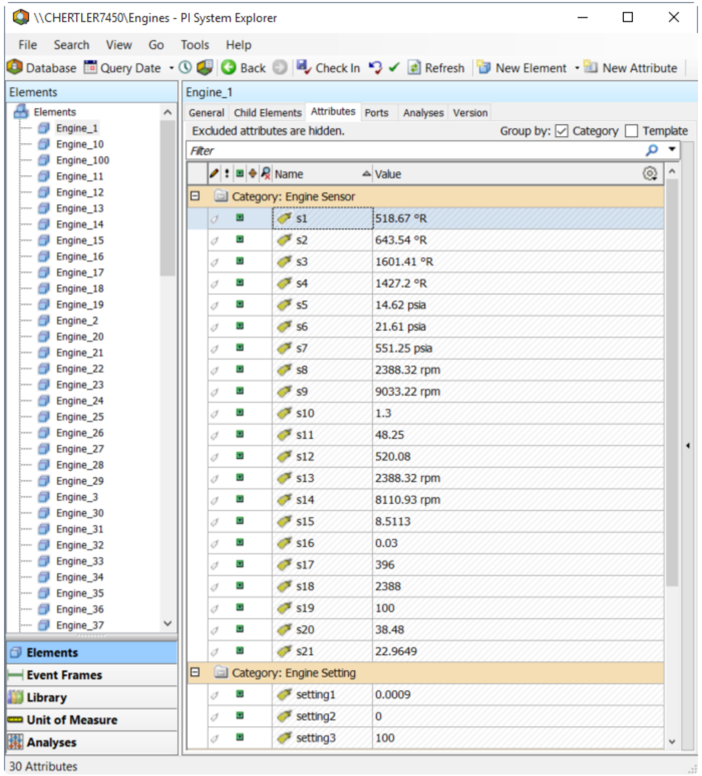
Step 4 - Implement the predictive model in AF Analytics, at scale, for all 100 engines.

Step 5 - Evaluate the predictive model using the PI Integrator for BA and Power BI Desktop.

Step 1
PI Analytics to create Event Frames

Lab PI System and AF Model “Engines”

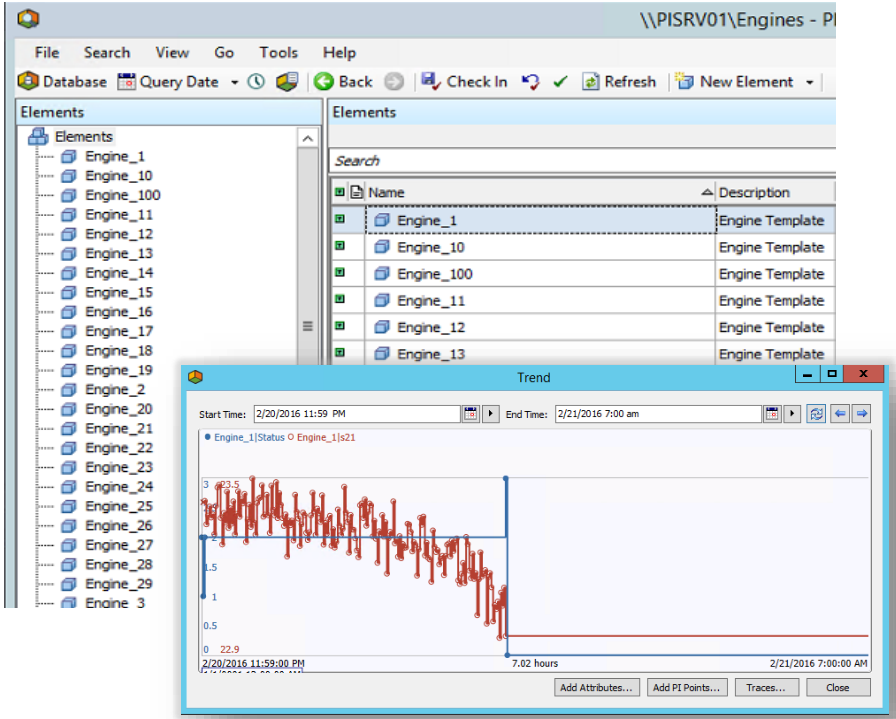
- Actual data for 100 engines
  - 21 sensors
  - 3 settings



*A. Saxena, K. Goebel, D. Simon, and N. Eklund, “Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation”, in the Proceedings of the Ist International Conference on Prognostics and Health Management (PHM08), Denver CO, Oct 2008.

Lab PI System and AF Model “Engines”

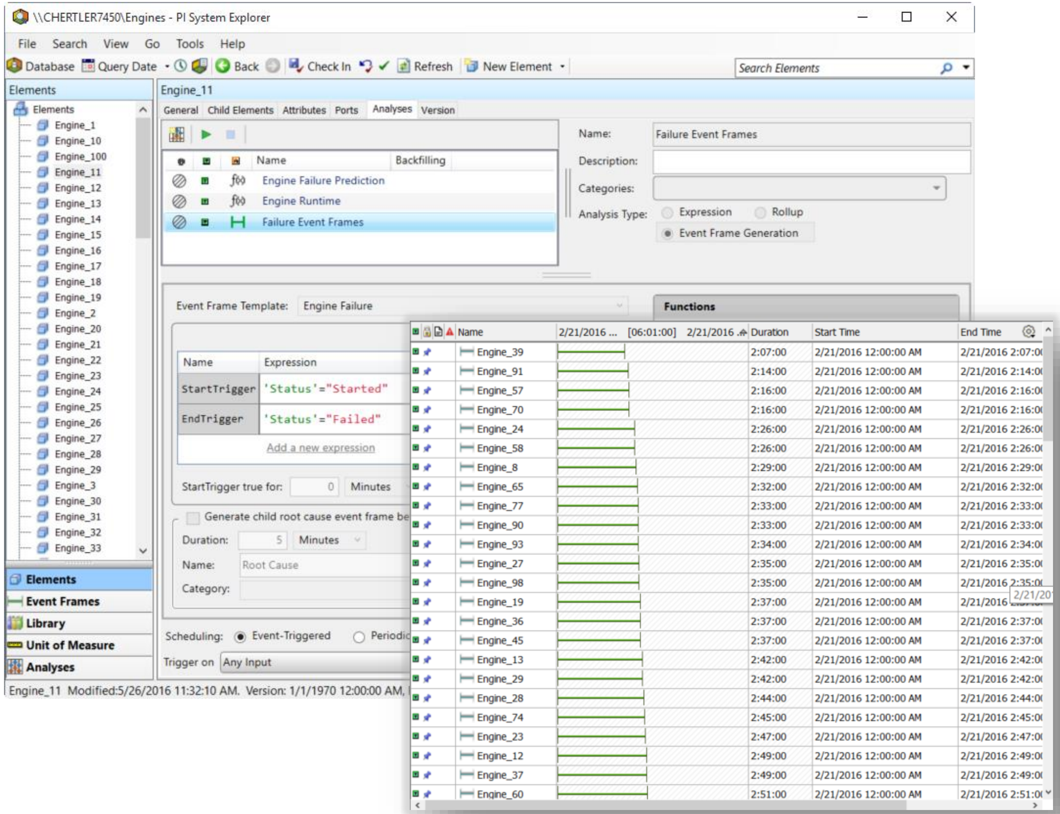
- Actual data for 100 engines
  - 21 sensors
  - 3 settings
- Operating time to failure varies
  - Start time is always 2/21/16 12 am
  - Failure times are no later than 2/21/16 7:00 am
- Operating status
  - “Running”, “Failed”, “Stopped”



*A. Saxena, K. Goebel, D. Simon, and N. Eklund, “Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation”, in the Proceedings of the Ist International Conference on Prognostics and Health Management (PHM08), Denver CO, Oct 2008.

Event Frames for Engine Failure

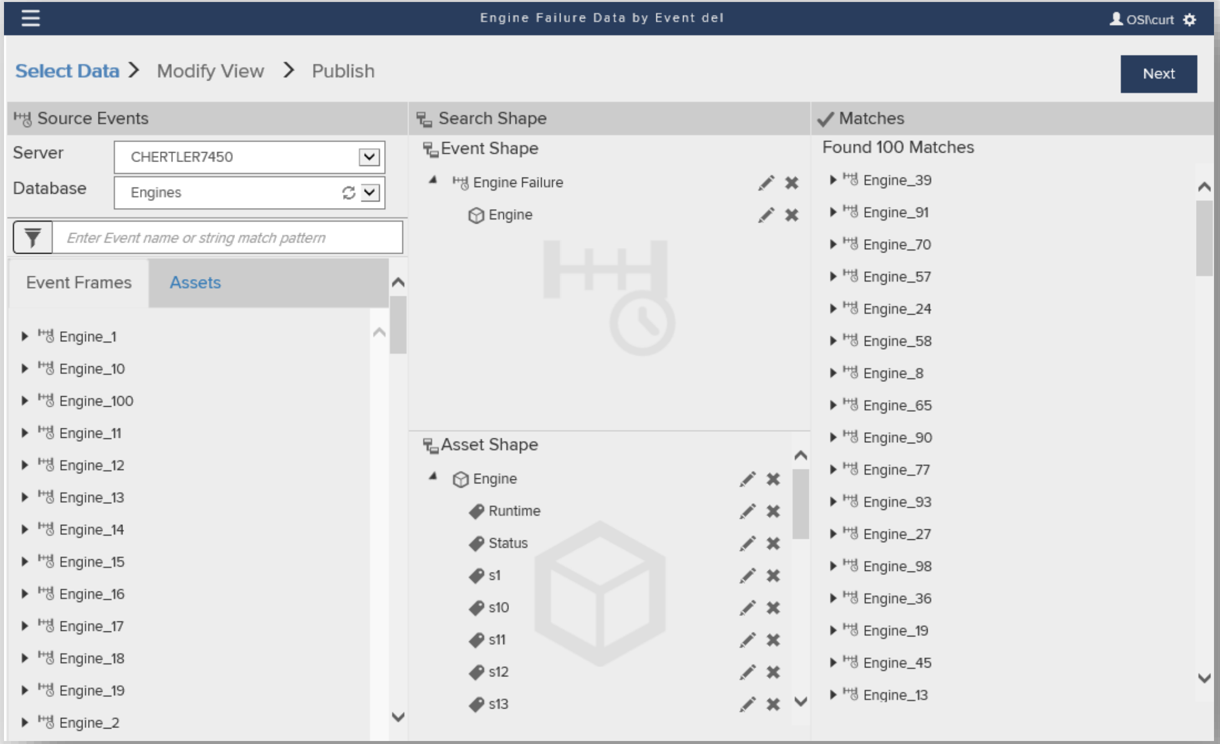
- Create Event Frame template.
- Add “Event Frame Generation” analysis to “Engine” template.
    - StartTrigger: ‘Status’ = “Started”
    - EndTrigger: ‘Status’ = “Failed”
- Backfill analysis to generate Event Frames for each engine.



Step 2
PI Integrator to publish Event View

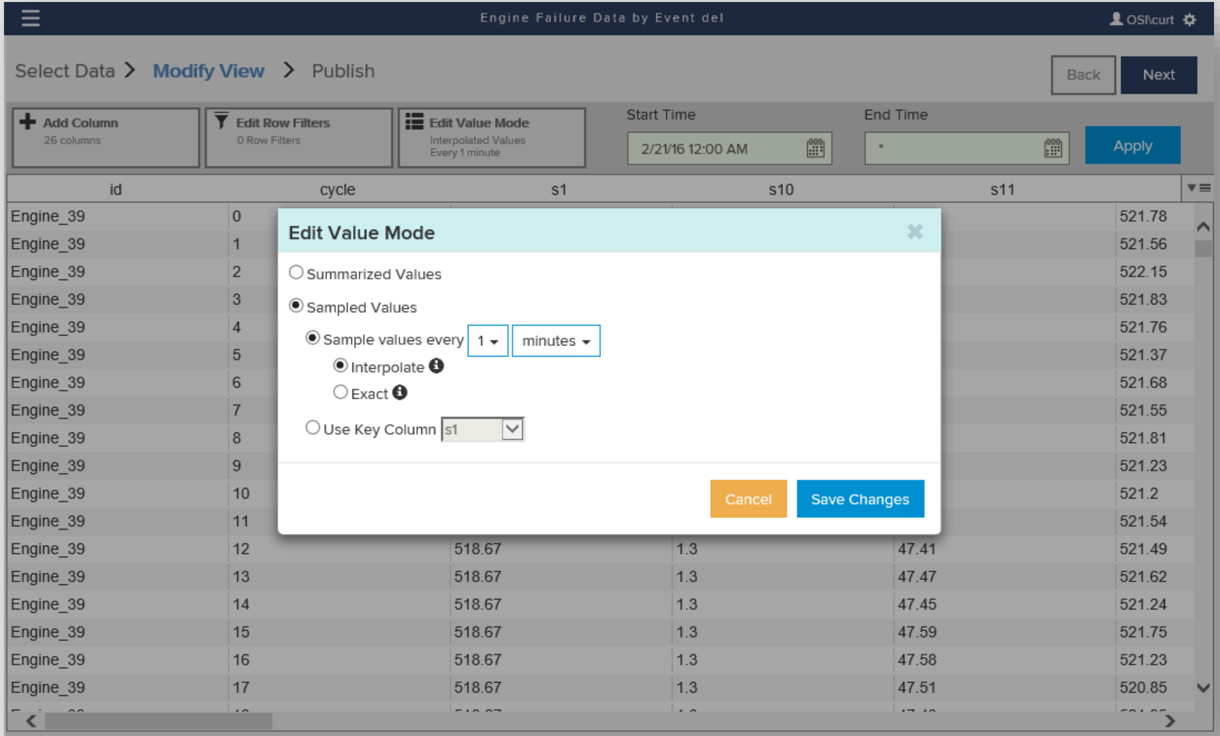
PI Integrator for Business Analytics - Select Data

- Create a PI Event View published as a text file.
- “Select Data”
  - Event Frames
  - Asset Template
  - Attributes



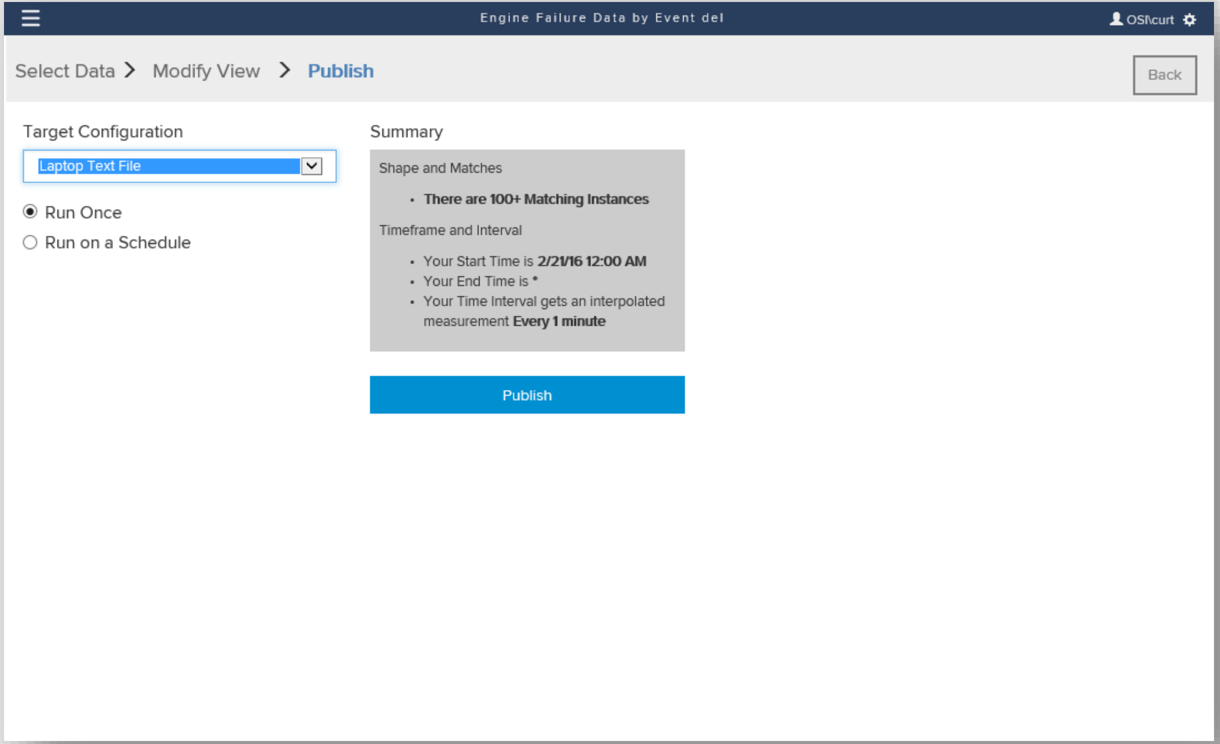
PI Integrator for Business Analytics – Modify View

- Create a PI Event View published as a text file.
- “Select Data”
  - Event Frames
  - Asset Element
  - Attributes
- “Modify View”
  - One minute samples



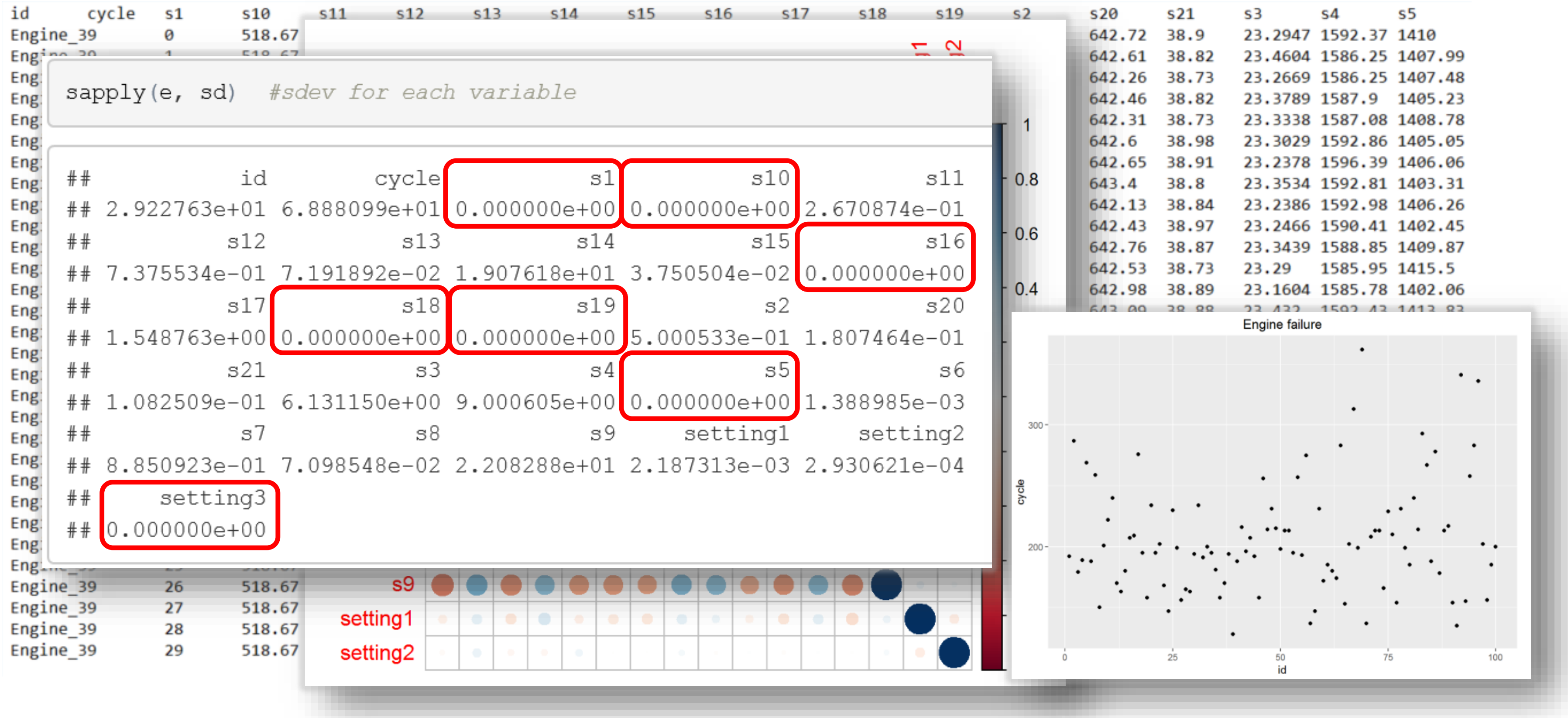
PI Integrator for Business Analytics – Publish

- Create a PI Event View published as a text file.
- “Select Data”
  - Event Frames
  - Asset Element
  - Attributes
- “Modify View”
  - One minute samples
- “Publish”
  - Create text file



Step 3
R script to derive predictive analytic

R Script Summary - Review Engine Dataset



R Script Summary – Remaining Useful Life

Remaining Useful Life (RUL) = (Event Frame Duration – Cycle) + 1

(Example, for engine (id) 1: 191 - 1 – 1)

id	cycle	s11	s12	s13	s14	s15	s17	s2	s20	s21	s3	s4	s6	s7	s8	s9	setting1	setting2	rul
1	1	47.47	521.7	2388	8139	8.419	392	641.8	39.06	23.42	1590	1401	21.61	554.4	2388	9046	-0.0007	-0.0004	191
1	2	47.49	522.3	2388	8131	8.432	392	642.1	39.00	23.42	1592	1403	21.61	553.8	2388	9044	0.0019	-0.0003	190
1	3	47.27	522.4	2388	8133	8.418	390	642.4	38.95	23.34	1588	1404	21.61	554.3	2388	9053	-0.0043	0.0003	189
1	4	47.13	522.9	2388	8134	8.368	392	642.4	38.88	23.37	1583	1402	21.61	554.5	2388	9049	0.0007	0.0000	188
1	5	47.28	522.2	2388	8134	8.429	393	642.4	38.90	23.40	1583	1406	21.61	554.0	2388	9055	-0.0019	-0.0002	187
1	6	47.16	521.7	2388	8133	8.411	391	642.1	38.98	23.37	1584	1398	21.61	554.7	2388	9050	-0.0043	-0.0001	186
1	7	47.36	522.3	2388	8132	8.397	392	642.5	39.10	23.38	1592	1398	21.61	554.3	2388	9059	0.0010	0.0001	185
1	8	47.24	522.5	2388	8131	8.408	391	642.6	38.97	23.31	1583	1401	21.61	553.9	2388	9041	-0.0034	0.0003	184
1	9	47.29	521.8	2388	8126	8.373	392	642.1	39.05	23.41	1591	1395	21.61	553.7	2388	9046	0.0008	0.0001	183
1	10	47.03	521.8	2388	8129	8.429	393	641.7	38.95	23.47	1591	1400	21.61	553.6	2388	9052	-0.0033	0.0001	182
1	11	47.15	521.4	2388	8141	8.434	392	642.3	38.94	23.48	1582	1401	21.61	554.5	2388	9050	0.0018	-0.0003	181
1	12	47.18	521.8	2388	8134	8.394	391	642.1	39.06	23.37	1583	1400	21.61	554.5	2388	9049	0.0016	0.0002	180

R Script Summary – Principal Components

Extract principal components

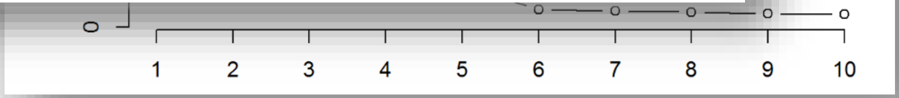
```
e.odd.pca = prcomp(e.odd.obs, scale = T, center = T)  #fit principal components (PC), use only odd engine data

su
```

```
# get pc1 equation
pc1eq = ""
for (j in 1:17) {
    pc1eq = cat(sep = "", pc1eq, "+(", "'", names(e.odd.pca$center[j]), "'", "-(",
        e.odd.pca$center[j], ")", ")/", e.odd.pca$scale[j], "*", e.odd.pca$rotation[j,
            1])
}
```

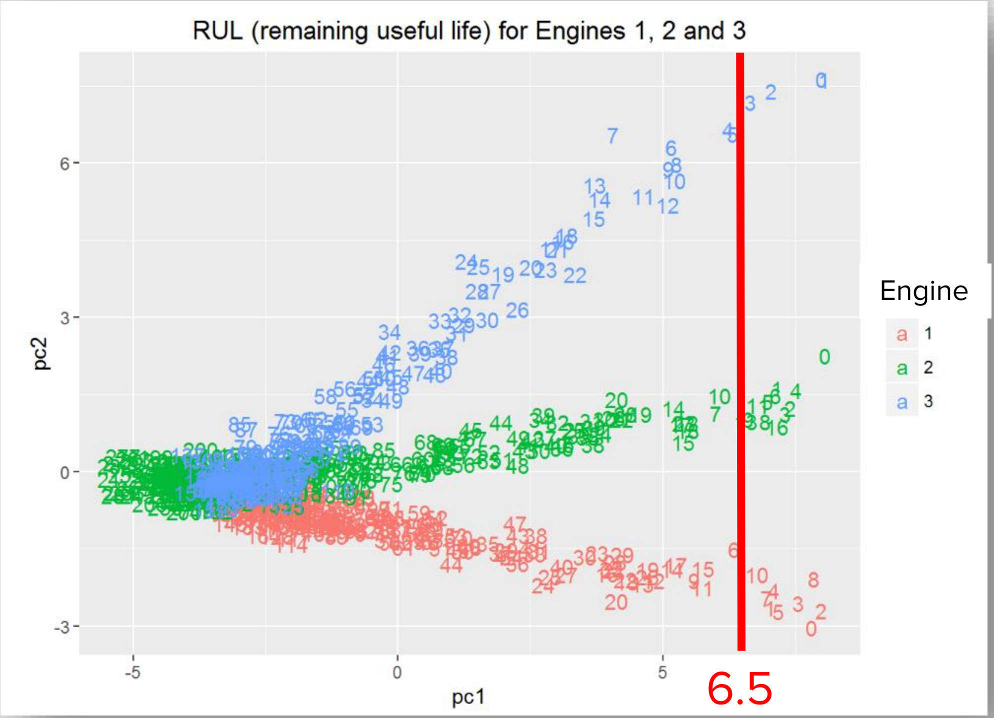
```
## +('s11'-(47.51488))/0.2701003*0.3090913+('s12'-(521.4901))/0.7517117*-0.3049236+('s13'-(2388.09))/0.07484883*
0.2845465+('s14'-(8143.502))/19.7965*0.04163657+('s15'-(8.438634))/0.03782789*0.2868222+('s17'-(393.0714))/1.5619
64*0.2685557+('s2'-(642.638))/0.5043607*0.2734667+('s20'-(38.83337))/0.1812555*-0.2819219+('s21'-(23.29963))/0.10
83872*-0.2834525+('s3'-(1590.048))/6.186916*0.2604444+('s4'-(1408.104))/9.077463*0.3006121+('s6'-(21.60976))/0.00
1539259*0.06360376+('s7'-(553.4522))/0.8983562*-0.2995252+('s8'-(2388.091))/0.07388822*0.2847322+('s9'-(9064.65
1))/22.72082*0.08204075+('setting1'-(-3.554925e-05))/0.002184843*0.003580013+('setting2'-(5.022518e-06))/0.000293
1999*0.003136759
```

```
##
##
##
##
##
##
##
##
##
##
##
##
##
```



R Script Summary – Predictive Approach

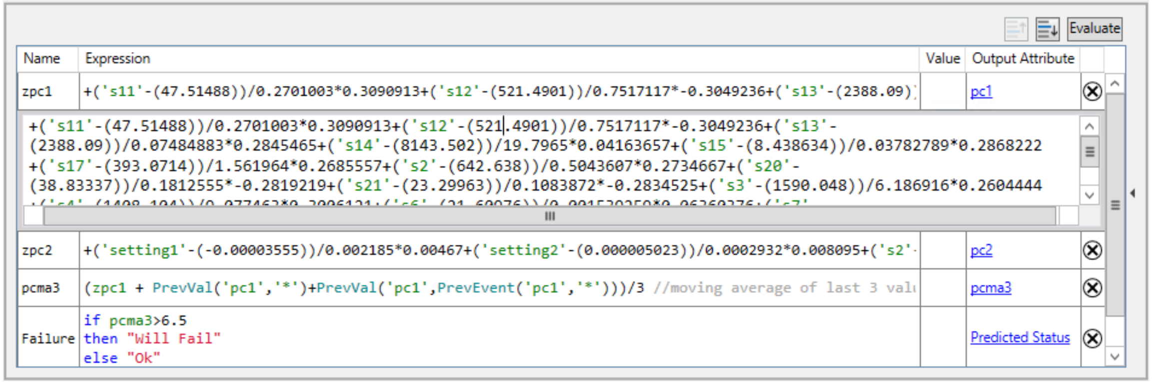
- Calculate pc1 in real time for each engine.
- If pc1 is greater than a limit of 6.5, post warning in digital state tag.

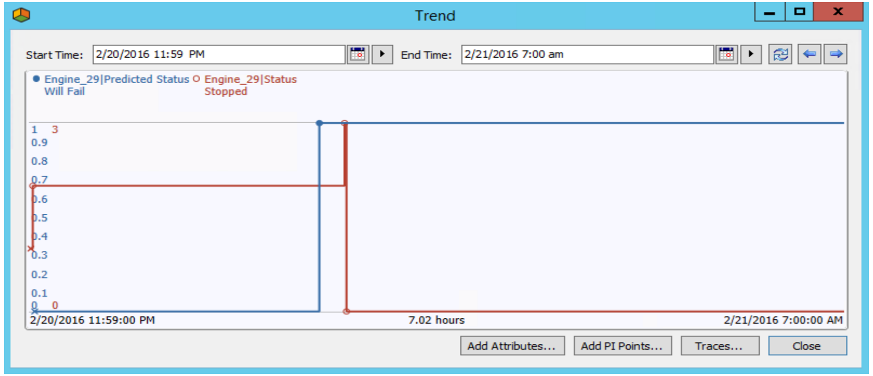


Step 4
PI Analytics to test and operationalize analytic

Operationalizing in AF Analytics

- Copy R model into Engine analysis template.
- Use AF Analytics to scale up model for all 100 engines.
- Backfill calculation, trend Status and Predicted Status attributes check for sufficient advanced warning.

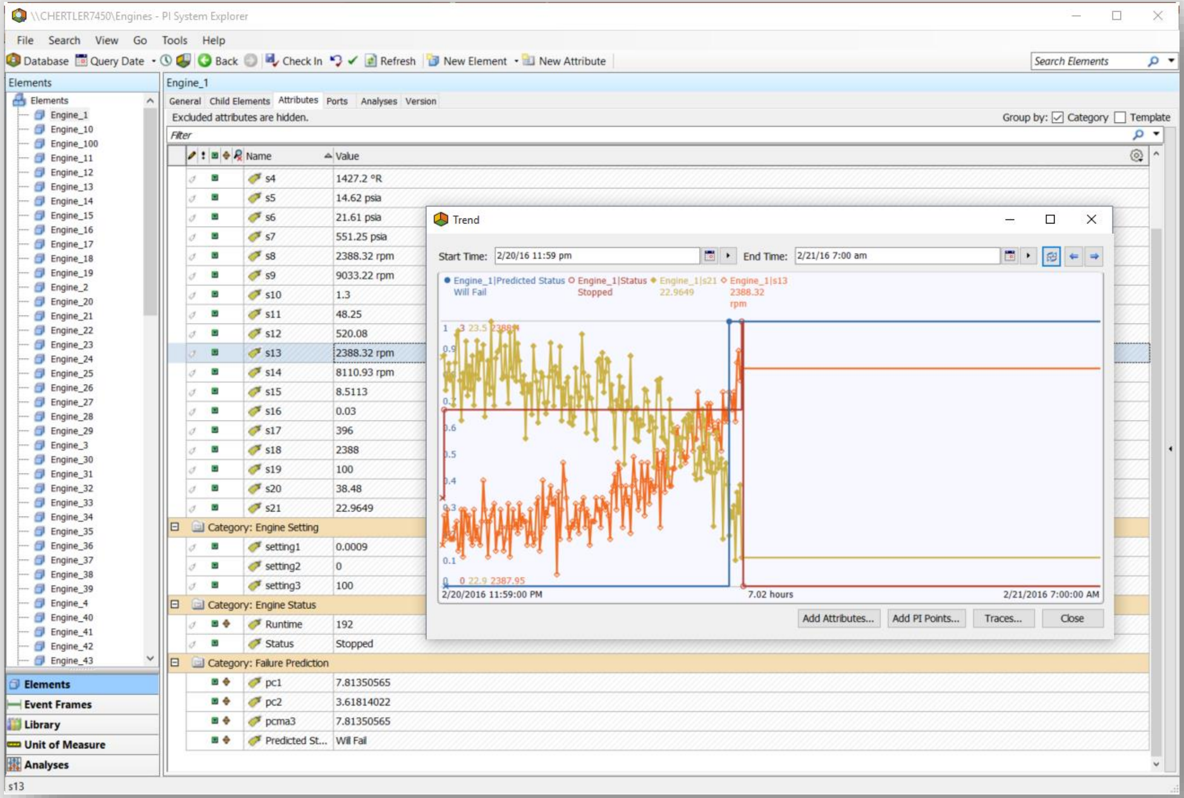




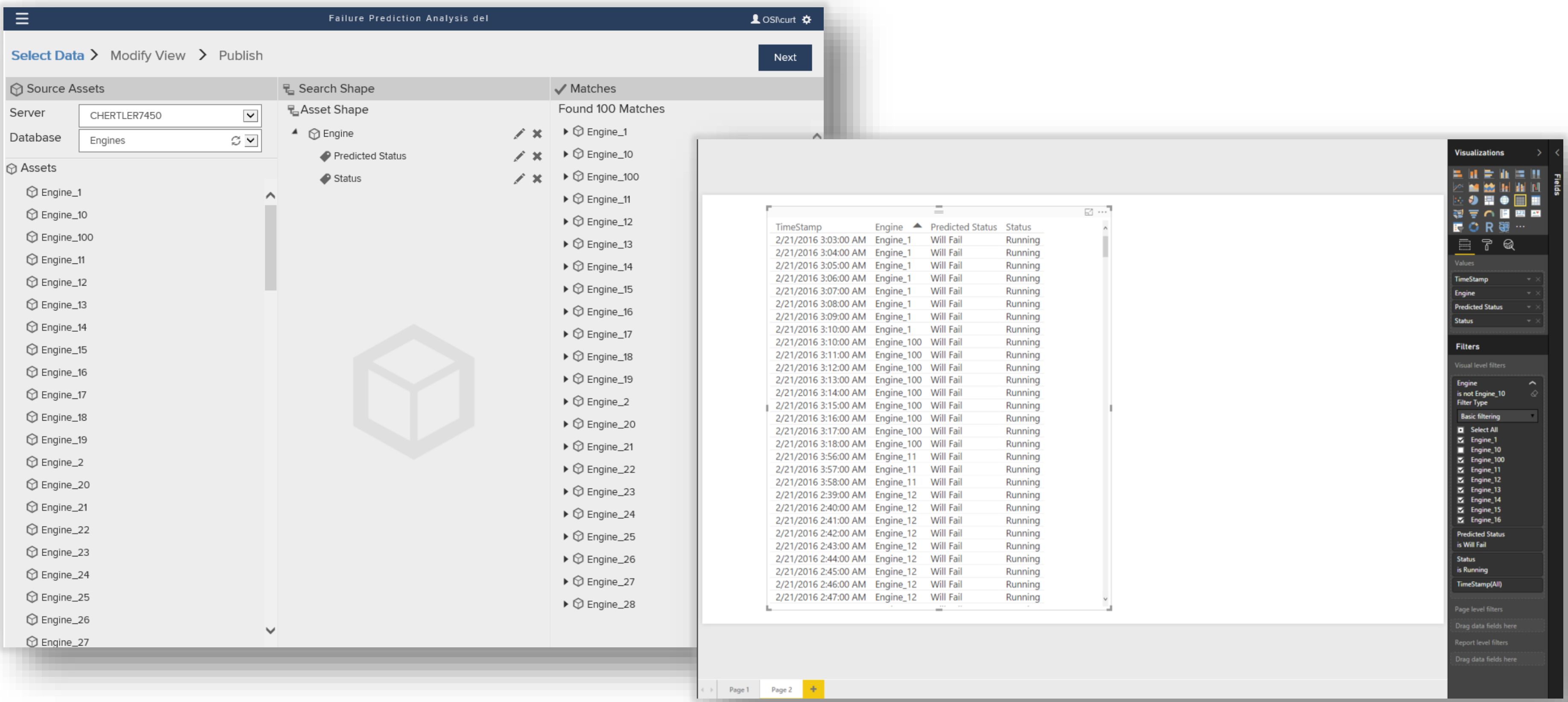
Step 5
Power BI Desktop to evaluate analytic

Evaluating the Prediction for All 100 Engines

- Use trending tool in PI System Explorer to evaluate on an engine-by-engine basis.
- PI Integrator with Power BI Desktop provides a much more efficient approach.



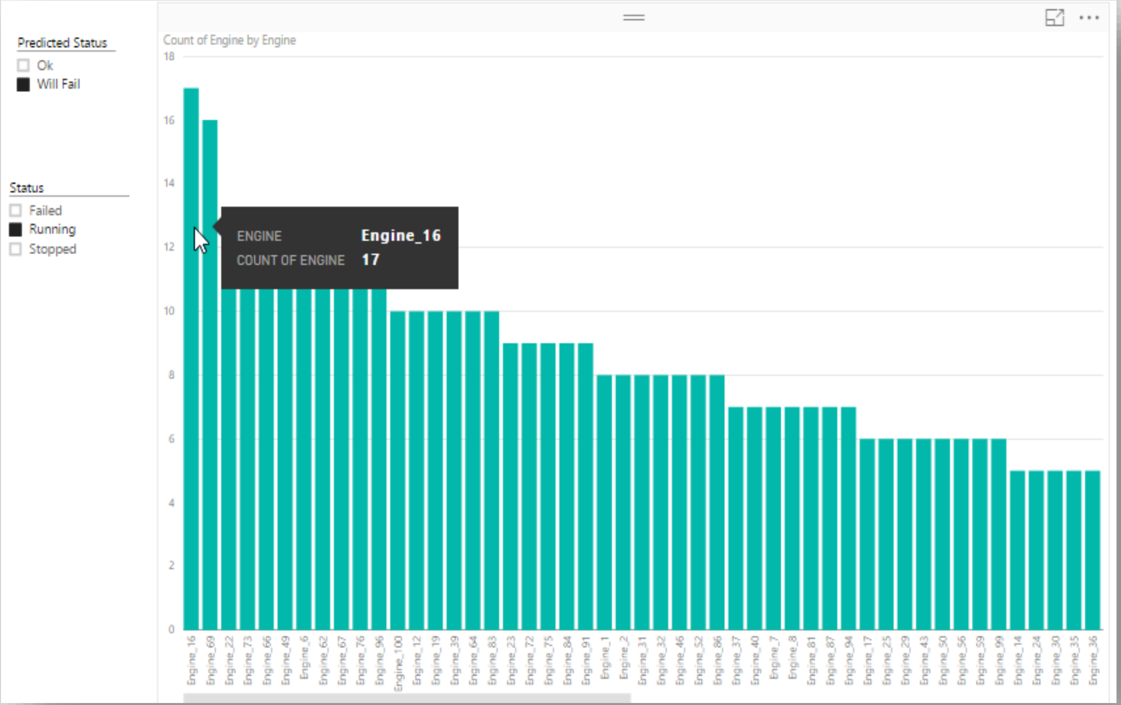
Evaluating the Prediction for All 100 Engines



Evaluating the Prediction for All 100 Engines

- Use the PI Integrator for BA to create a second dataset containing the Status and Predicted Status for all engines.

- Create a filtered bar graph in Power BI showing the amount of lead time the prediction gives before actual failure occurs.



Useful Links

Microsoft Power BI Desktop
https://powerbi.microsoft.com/en-us/downloads

Microsoft R Application Network
https://mran.microsoft.com

Power BI Custom Visuals
https://app.powerbi.com/visuals

Contact Information

Curt Hertler

curt@osisoft.com

Global Solutions Architect

OSIsoft

감사합니다

谢谢

Danke

Merci

Gracias

Thank You

ありがとう

Спасибо

Obrigado