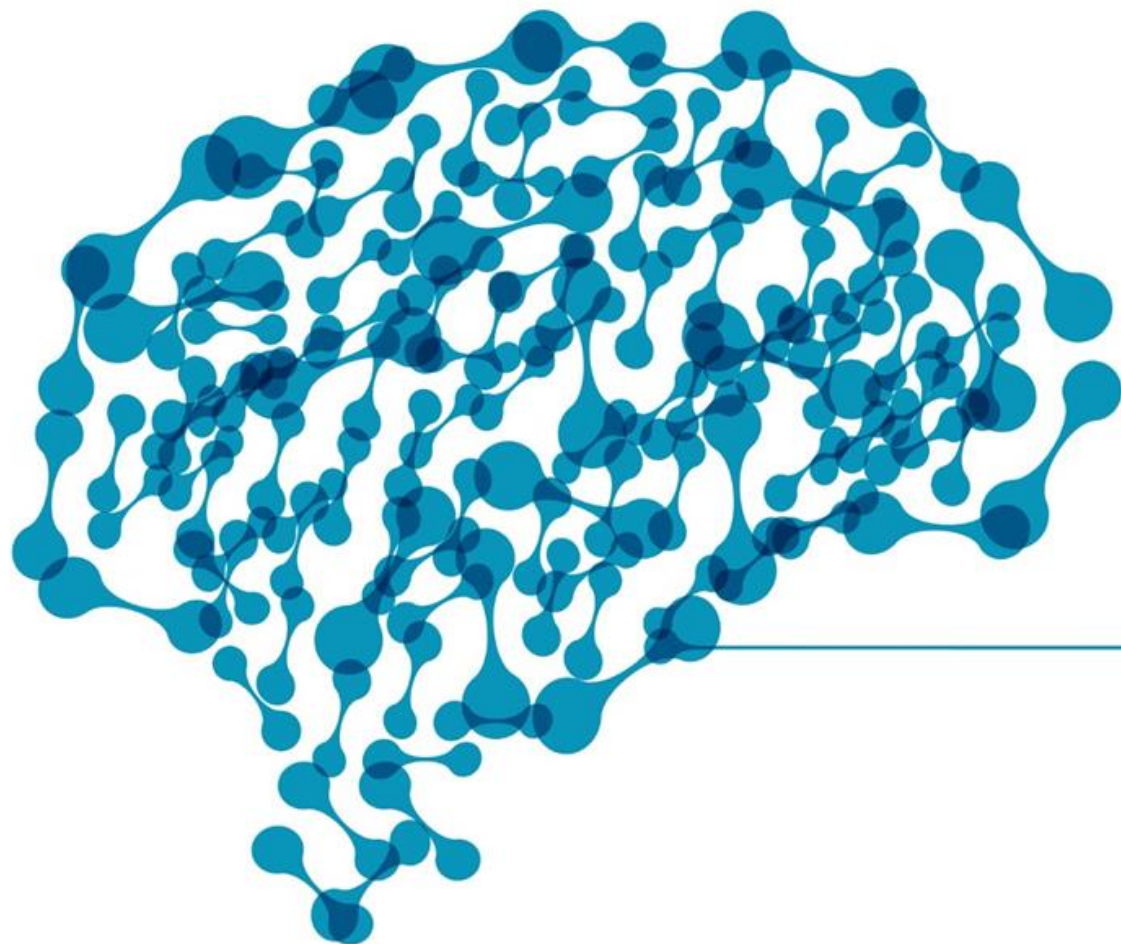




EMPOWERING BUSINESS TO
EMBRACE MACHINE INTELLIGENCE

Project Summary

Predictive Maintenance

At Olympic Dam Copper Smelter

PREDICTIVE MAINTENANCE PROJECT

Collaboration between CSIRO and Consilium funded by the South Australian Government and BHP

Objectives

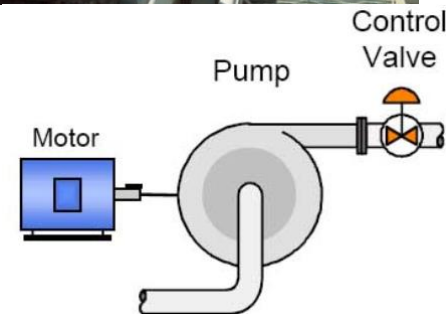
- Develop algorithms to predict maintenance need at Olympic dam smelter.
Transition proactive/reactive maintenance to predictive.
- Utilise only *existing* sensor infrastructure and data.
- Commercial plan to deliver data analytics to the mining industry.
- Grow Consilium's capacity in data analytics for non-defence industry.

MAINTENANCE MATURITY MODEL

	4. Predictive maintenance	Data analytics on sensor data
	3. Condition-based monitoring	Watch key sensors
	2. Preventive Maintenance	Fixed time or usage
	1. Reactive Maintenance	Run to fail

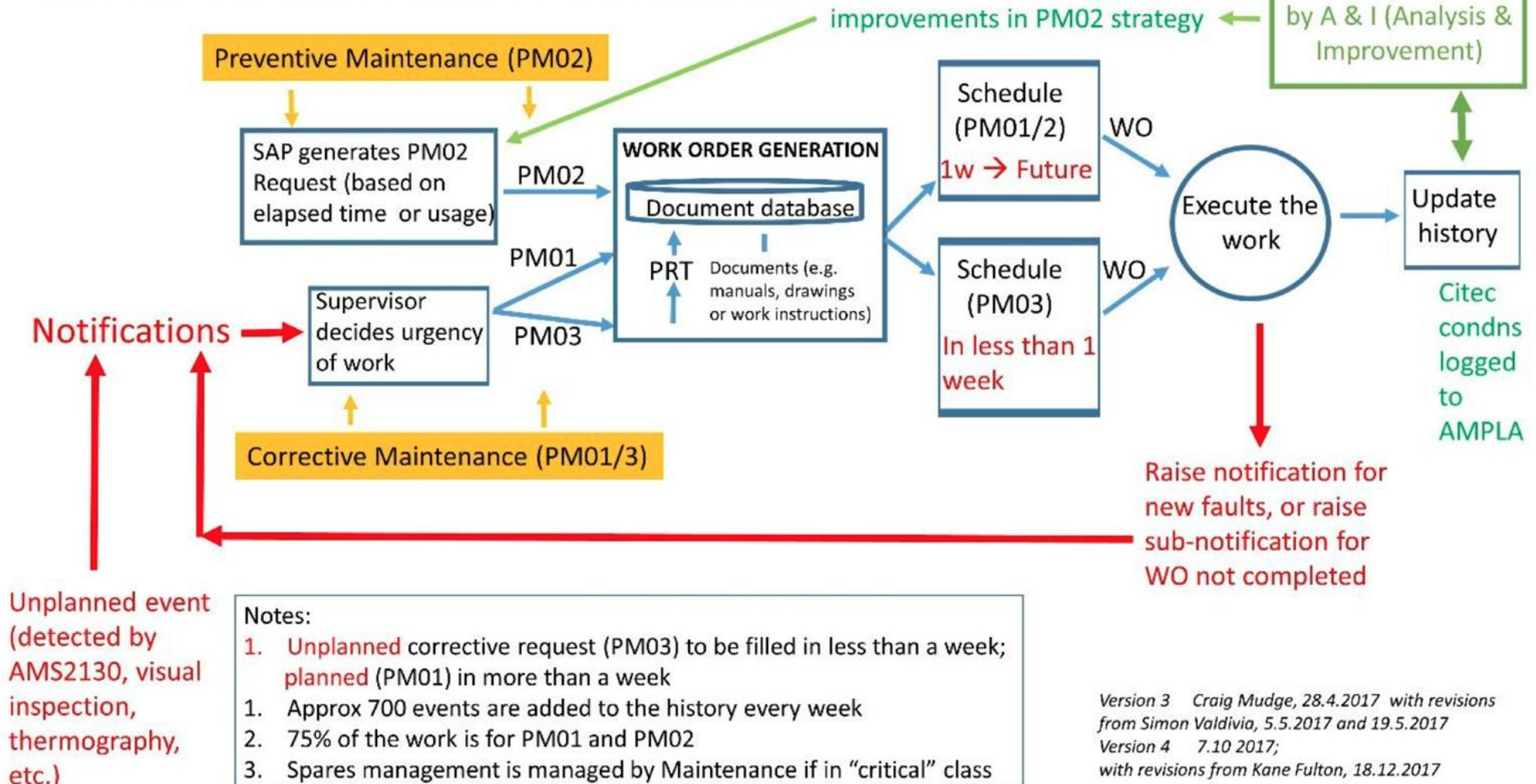
SENSOR DATA

1. Vibration
2. Temperature
3. Pressure
4. Oil contents, e.g., iron filings – magnetic plug
5. Oil level
6. Filter inspections
7. Current draw on motor
8. Voltage level on motor
9. Age
10. History
11. Ultrasound – revealing anomalies in material thickness (wear or corrosion) and internal flaws
12. Acoustic emission – detecting and locating cracks during their formation



MAINTENANCE PROCEDURE

Information flow in OD smelter maintenance system



Version 3 Craig Mudge, 28.4.2017 with revisions from Simon Valdivia, 5.5.2017 and 19.5.2017
Version 4 7.10.2017; with revisions from Kane Fulton, 18.12.2017

- Flash Furnace (4321)
- Electric Furnace (4331)
- Offgas & Dust (4341)

- Flash Furnace (4321)
- Electric Furnace (4331)
- Offgas & Dust (4341)

- 29 Fans
- 35 Pumps, 4 Sumps

- 29 Fans
- 35 Pumps, 4 Sumps

- Vibration
- Temperature
- Power & Current
- Speed
- Flow
- Pressure

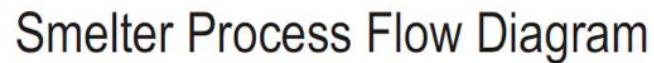
- Vibration
- Temperature
- Power & Current
- Speed
- Flow
- Pressure

- Notifications (NO)
- Work Orders (WO)

- Notifications (NO)
- Work Orders (WO)

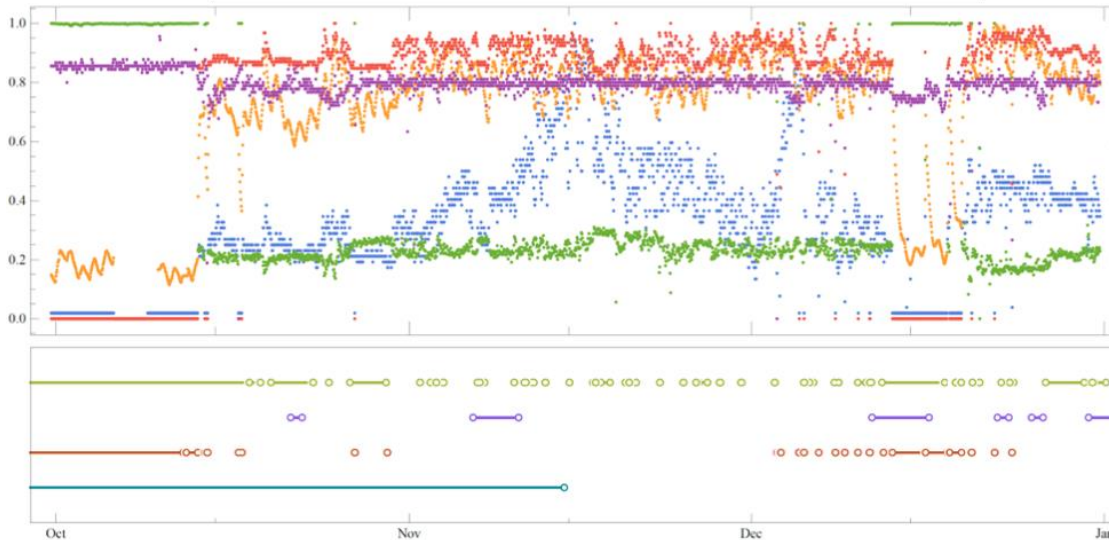
- AMPLA - events
- Manuals
- Assay Data

- AMPLA - events
- Manuals
- Assay Data



DATA

TIMESERIES



- BearingVibA
- Temp1
- FanSpeed
- InDuctPres
- DraftControl
- FlashFurnaceDowntime
- FanMaintenance
- FanDowntime
- Campaigns

TEXTUAL

27.05.2016 02:23:21 UTC

Engineering Requirement Details:

Describe the requirement in Detail:

FA1019's bearings are failing and require change out in the June shutdown. This fan is a critical fan for the safe operation of the furnace. This job has been identified as requiring extra quality control to ensure the fan remains reliable and pre-mature failure of the bearings is minimised.

This is required for the June shut which starts on the 17/6/2016.

Describe the need for the requirement, and any expected benefits (e.g. HSEC benefit, equipment reliability benefit, cost benefit):

This is a critical fan for the smelter operation and these bearings are not changed regularly. The risk of pre-mature failure needs to be minimised as much as possible.

Describe all risks associated with the requirement and how each risk will be managed:

Risk associated with the work will be covered through the jobs hazard analysis.

List all key contacts (stakeholders) associated with the Engineering Requirement

- Area maintenance Superintendent
- A&I engineer
- Shutdown Planner

Scope of work:

What objects are in scope of the requirement or out of scope?
Create an ITP for the change out of the DE and NDE bearings on FA1019 that contains the key hold points to ensure the job is completed

correctly. Things to consider include;

- Tolerances
- Final greasing

Describe the specific work activities required to implement the requirement:
Create ITP

Describe all foreseen modifications required to existing documents (1SAP or non-1SAP document):
NA

Describe all foreseen modifications required to 1SAP master data:
NA

Attach supporting document such as detailed risk assessment (if already complete).

Engineering Requirement Coordinator comments:

28.05.2016 04:43:18

have emailed Craig Hall to specify of this noti is for replacing the bearings or to just create the ITP.

30.05.2016 02:14:08

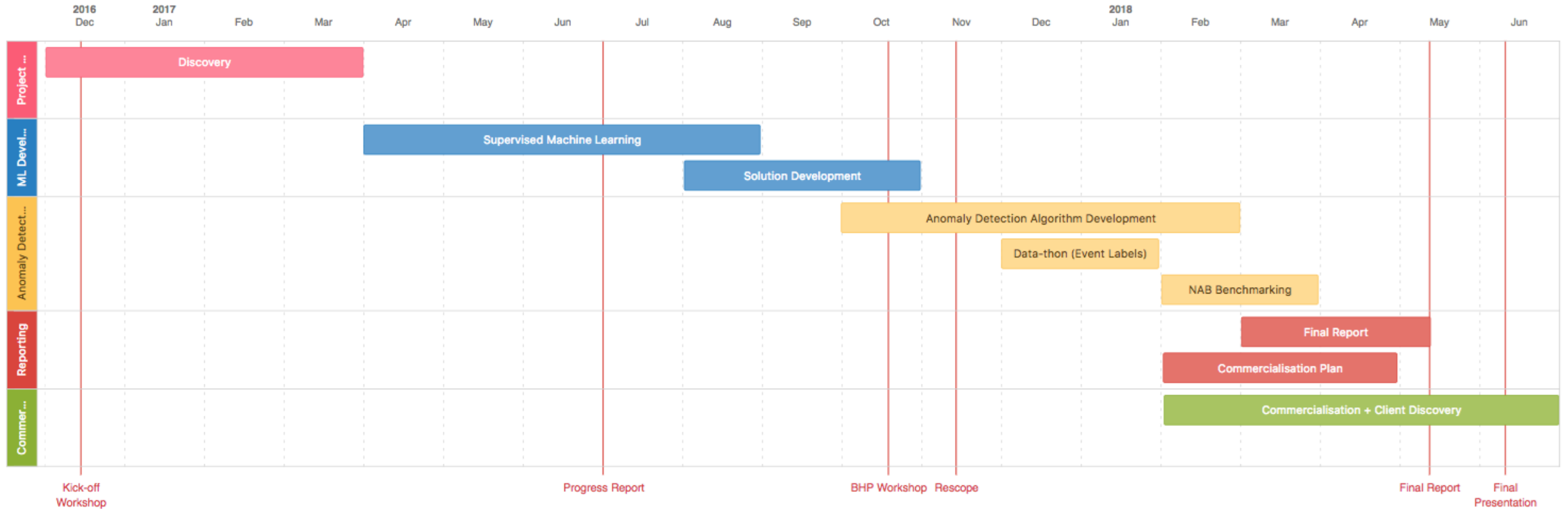
IA&I being a critical control for the FF material risk, the seal kits are not kept in stock. Sap says it's only a 7 day lead time, but, if we do have a complete failure of one or more of the 4 bearings (FA1018 & FA1019) we will need to replace the seals and won't want the fan to be down for a week. Is there something we can do to raise the minimum stock level to at least 2 kits?

02.06.2016 02:06:03

Assign to (SNAD) for 8hr to complete Tech Assessment;
Due 22/06/16.

16.06.2016 05:36:33 UTC
ITP attached.

PROJECT TIMELINE



Anomaly Detection Rescope

Predictive Maintenance

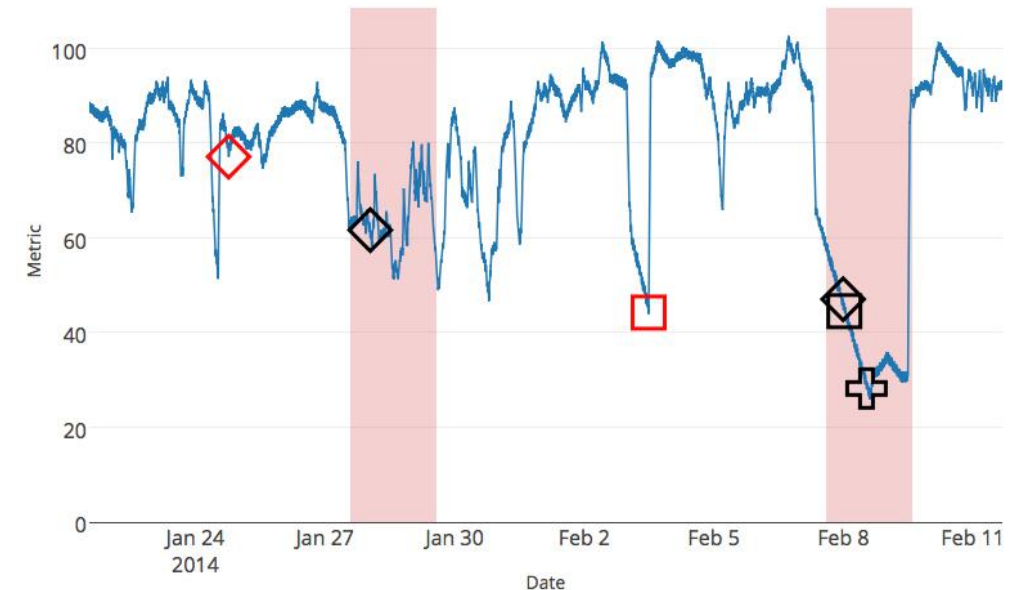
At Olympic Dam Copper Smelter

STEP APPROACH TO PREDICTIVE MAINTENANCE

Questions:

- Can we detect "significant" changes in asset (pump or fan) behavior using only the sensor data we have?
- Do these changes correlate with actual events identified in the smelter.
- What is observation window for these changes? Can they be identified prior to a manual inspection or before an existing alarm.

Motivation: Anomalous events provide an indication when the underlying behavior of the system deviates from its "normal" operation.



Idea: Anomaly Detection!

ANOMALY DETECTION CHARACTERISTICS

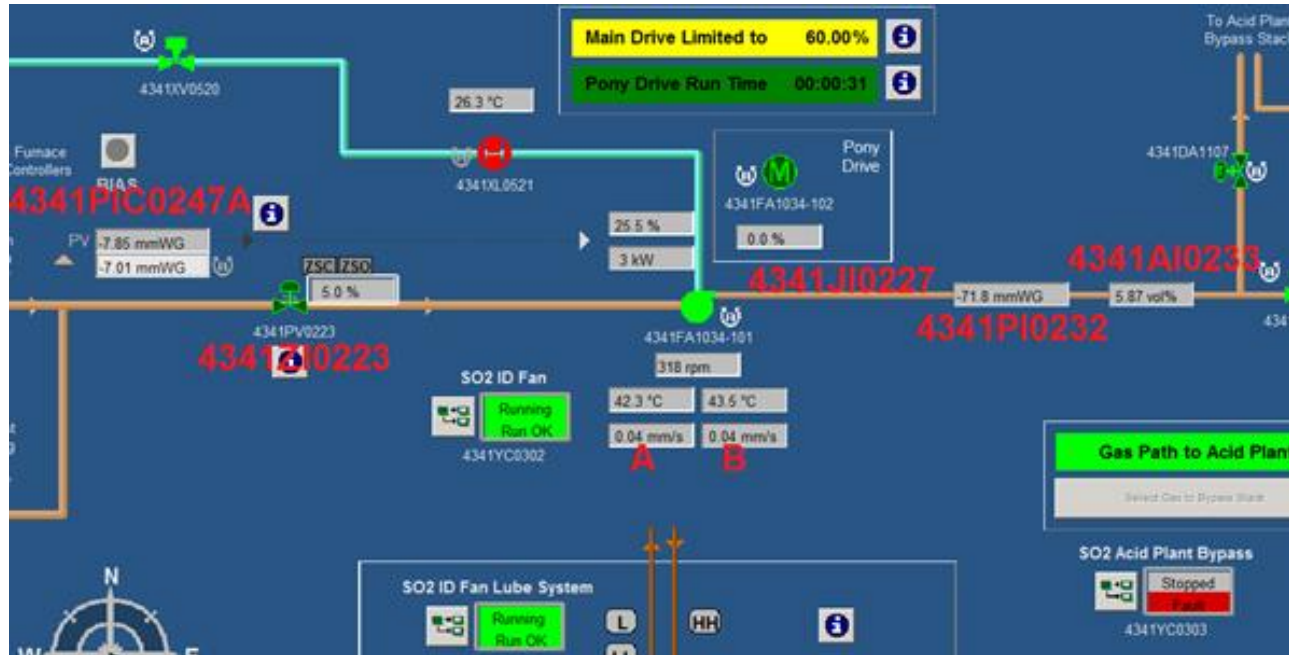
Ideal characteristics (Ahmad and Purdy 2017):

1. Predictions must be made online.
2. Learn continuously without a requirement to store the entire stream.
3. Run in an unsupervised, no labels or manual parameter tweaking.
4. Adapt to dynamic environments and concept drift.
5. Identify anomalies detections as early as possible.
6. Minimise false positives and false negatives.

Future Considerations

- Alternate more “robust” approaches than standard deviation.
- Handle (and identify) different types of anomalies.
- Pathway to improve solution after smelter upgrade., incorporate new data.
- Pathway to fully predictive system.
- Ensemble multiple anomaly detection approaches.
- Adjust for operator and maintenance interaction.
- Assess/score asset risk based on detections.

● ● ● ●



- Identifying Assets (Citect System)
 - Identify Fans and Pumps
 - Direct and 1-Step (upstream, downstream sensors)
 - Developed 'golden-list'

INTEGRATED DATASET

Asset Name	ASSET NO	# Tags	# Events
Concentrate Air Blower (Duty)	4321FA1006	8	7
Concentrate Air Blower (Standby)	4321FA1007	8	11
Combustion Sulphur Blower (Duty)	4321FA1008	8	6
Combustion Sulphur Blower (Standby)	4321FA1009	8	5
FF Hearth Cooling Fan 1	4321FA1018	2	13
FF Hearth Cooling Fan 2	4321FA1019	2	17
SO ₂ Fan	4341FA1034	15	49
Electric Furnace Off Gas Fan	4331FA1080	23	40
Waste Heat Boiler Feedwater Pump (Duty)	4341PU1053	7	17
Waste Heat Boiler Feedwater Pump (Standby)	4341PU1054	7	8
Waste Heat Boiler Circulating Pump (Duty)	4341PU1056	8	18
Waste Heat Boiler Circulating Pump (Standby)	4341PU1057	8	38

Time Series Data (Historian)

- Frequency #: Hour (original Minute)
- Date #: 2013-2017
- Test and Validation Dataset

Assets

- 8 Fans + 4 Pumps
- 7 Groupings
- 91 Tags

Tags

- Temperature (°C)
- Vibration (mm/s)
- Pressure (kPa)
- Speed (% , rpm)
- Airflow (Nm³/h)

Event Labels (Notifications, Work Orders)

- 229 Maintenance Events

ANOMALY DETECTION TOOLKIT

Developed Algorithms

- N-Sigma
- Multivariate Bayesian
- A LSTM (Long Short Term Memory) recurrent neural network.
- Hierarchical temporal memory based approach (Numenta)
- PCA
- LSTM_PCA

PLUS: Pre-packages anomaly detectors.

- Bayesian Change Point
- EXPOSE
- Relative Entropy
- Skyline

NUMENTA ANOMALY BENCHMARK

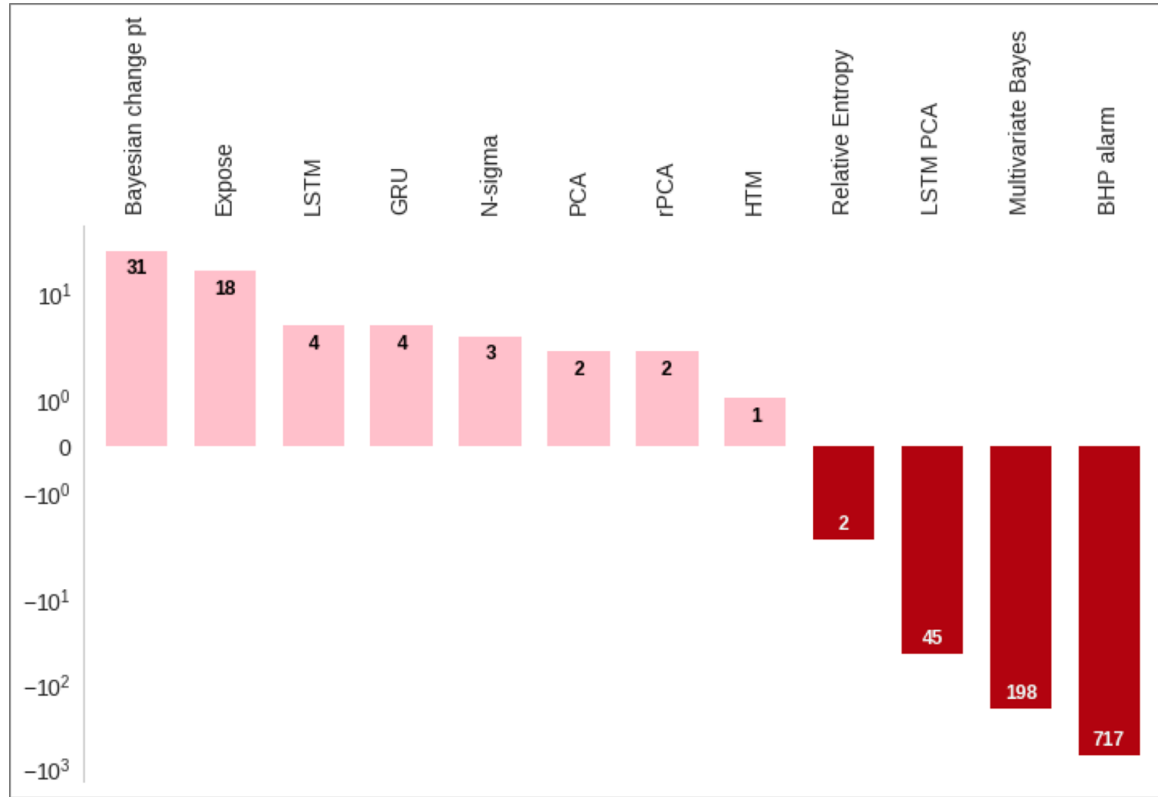
- Open source benchmark for comparing anomaly detectors
- Key Features
 - Easy to deploy python code repository.
 - Ability to incorporate new data series.
 - Handles time series of variable length and data frequency.
 - Functionality to optimise score for a given algorithm $\Rightarrow$ best possible score.
 - Uses anomaly windows (regions) for truth labels allowing for temporal ambiguity.
 - Rewards early detection of anomalies.
 - Scoring scheme that both rewards *positive detections* and penalise *incorrect detections*.
 - Provides multiple scoring schemes for different objectives
 - balanced,
 - minimise false positive (reduce number of false alarms),
 - minimise false negative (don't miss failures on life-critical systems).

Lavin, A. and Ahmad, S., 2015, December. Evaluating Real-Time Anomaly Detection Algorithms--The Numenta Anomaly Benchmark. In *Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on* (pp. 38-44). IEEE.

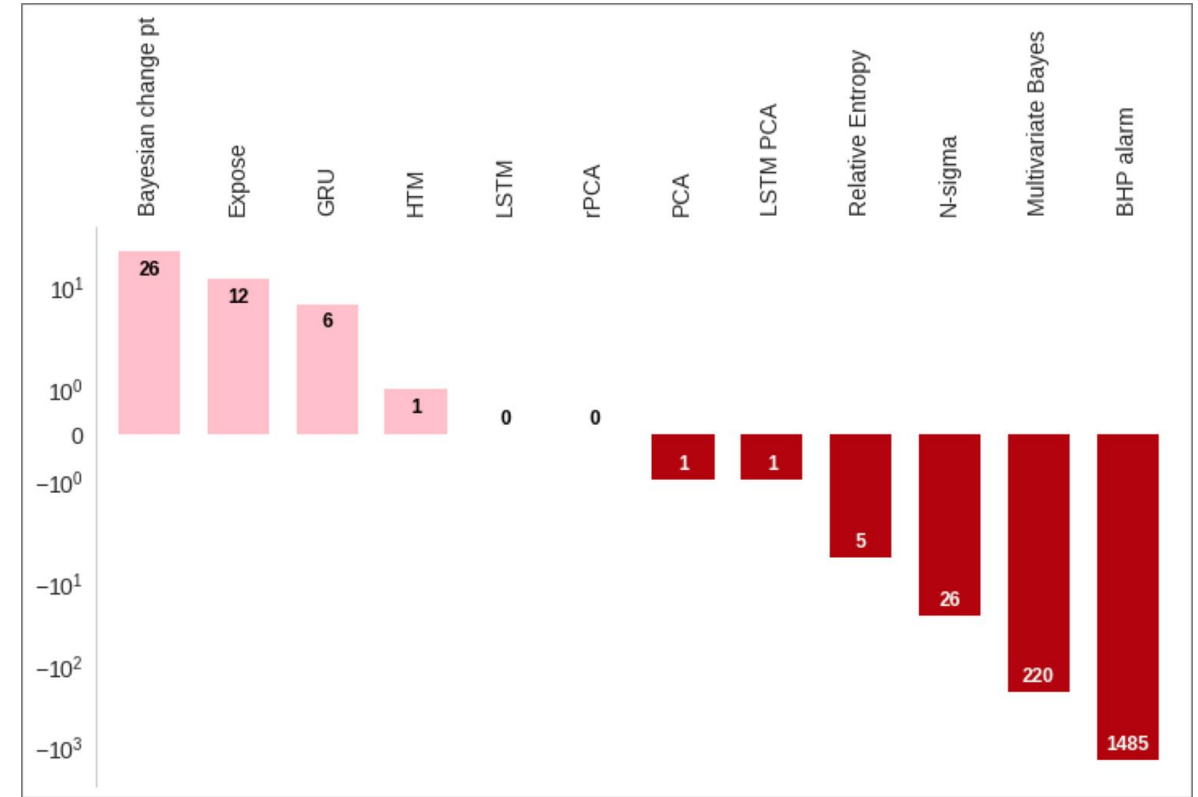
NAB BENCHMARK RESULTS

	OFF-GAS FAN (FA1080) Anomaly Detector											
Score Scheme	N-Sigma	Multivariate Bayesian	LSTM	HTM	PCA	rPCA	GRU	LSTM PCA	BHP Alarm (proxy)	Bayesian Change Point	Relative Entropy	Expose
Standard	3	-198	4	1	2	2	4	-45	-717	31	-2	18
Low False Negative	11	-120	6	2	3	3	7	-28	-474	41	4	27
Low False Positive	-17	-426	3	-1	2	2	2	-93	-1447	14	-18	2
	S02 FAN (FA1034) Anomaly Detector											
Score Scheme	N-Sigma	Multivariate Bayesian	LSTM	HTM	PCA	rPCA	GRU	LSTM PCA	BHP Alarm (proxy)	Bayesian Change Point	Relative Entropy	Expose
Standard	-26	-220	0	1	-1	0	6	-1	-1485	26	-5	12
Low False Negative	-10	-143	0	3	-0	0	11	0	-984	42	1	19
Low False Positive	-70	-452	-1	-2	-1	-1	2	-1	-2987	-6	-24	0

NAB BENCHMARK RESULTS



Off Gas Fan



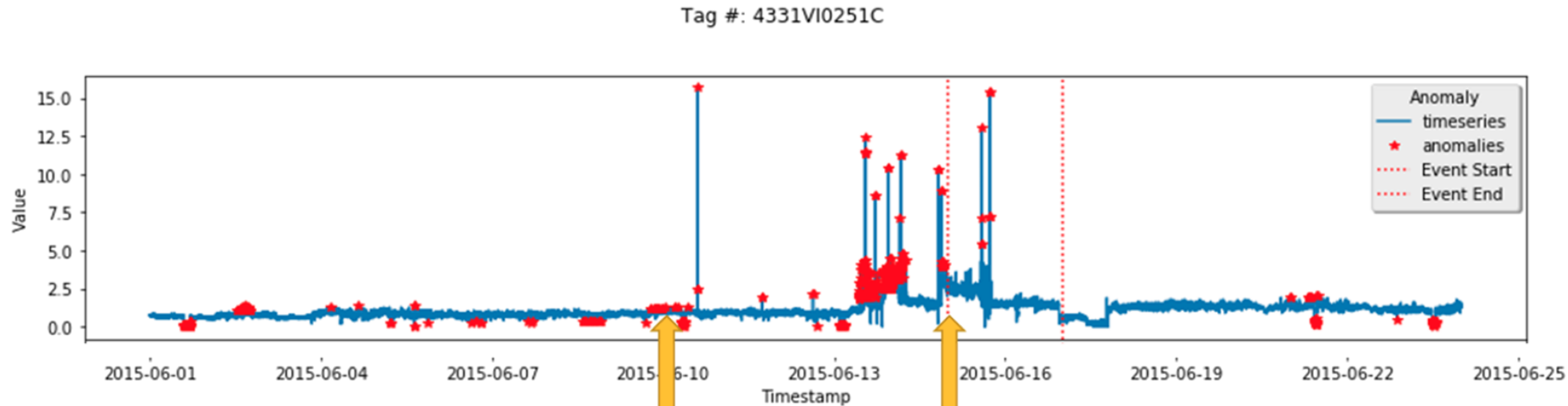
SO₂ Fan

NAB RESULTS

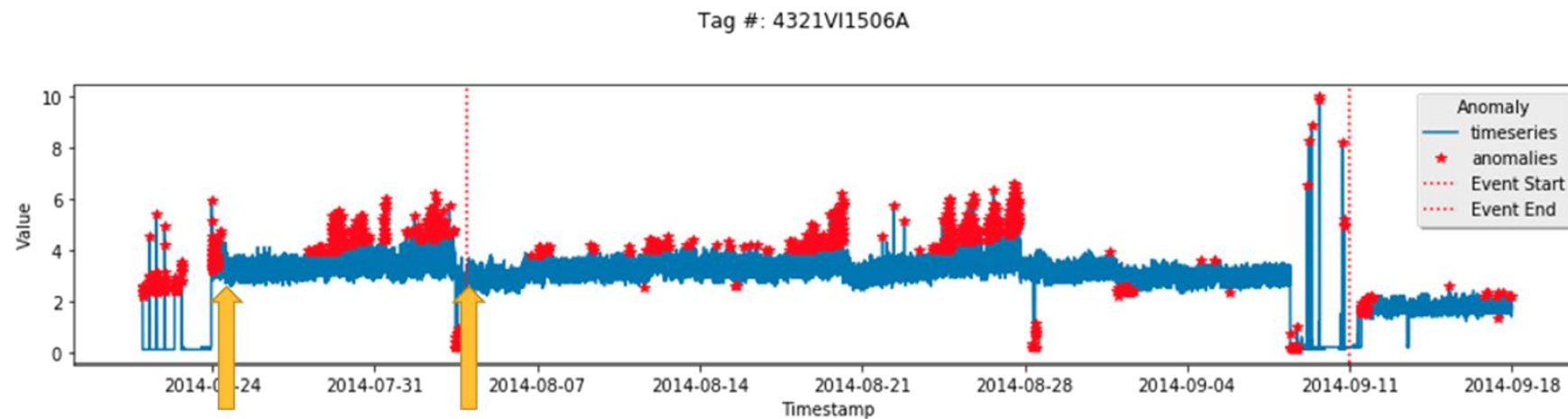
- Best Performing: Bayesian Change Point (Pre-Packaged)
- Worst Performing: existing Alarm System
- Biggest Issue: High False Positive - false alarms
- Detected almost all (human) labelled events
- Need to balance between true and false detections
 - Unlikely to find a gold solution
- Difficulties
 - Event labels are not definitive
 - High level of operator interaction
 - Maintenance events differ in priority and time period for rectification
 - Inconsistent sensor array setup
 - Data resolution

ANOMALY DETECTION EXAMPLE

Example: 3-Sigma Anomaly Detector



Off Gas Fan
NDE Bearing
Replacement



Hearth Cooling
Bearing Grease

CONCLUDING REMARKS

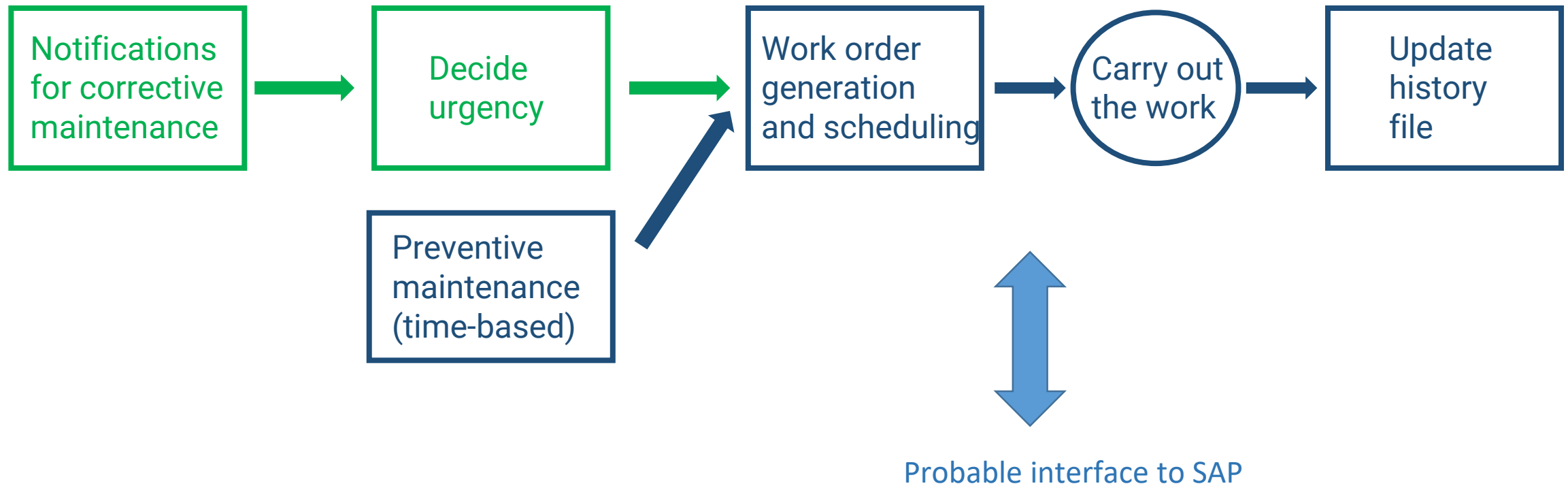
- Data
 - Developed a unique data set
 - Failure (or maintenance action required) is hard to define
 - Recommend: build data capture into business processes
 - Recommend: vibration sensors with frequency
- Algorithms
 - Anomaly detection is $10^4 \times$ better than magnitude alarms
 - Remaining useful life requires more historical failures
- People and processes
 - Close engagement with the end users

Commercialisation

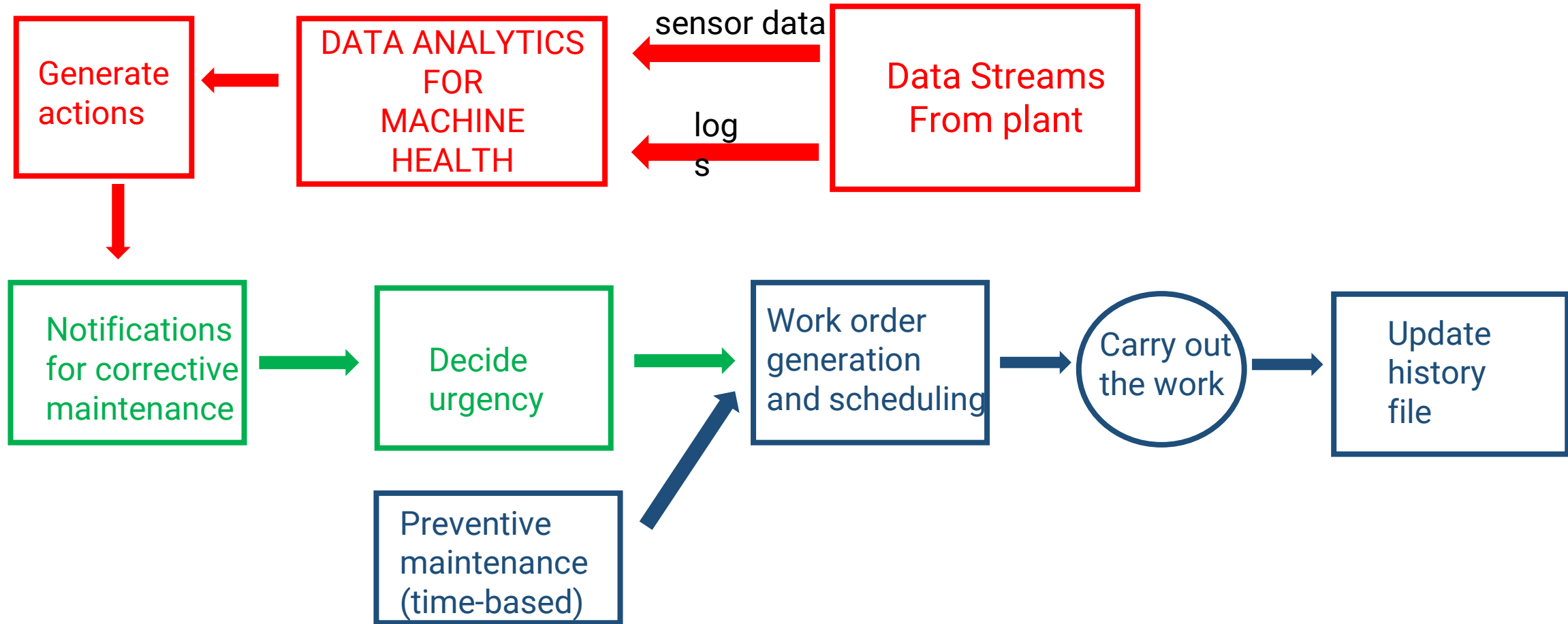
Predictive Maintenance

At Olympic Dam Copper Smelter

CURRENT MAINTENANCE MANAGEMENT SYSTEM



ADDING A DATA ANALYTICS TOOL

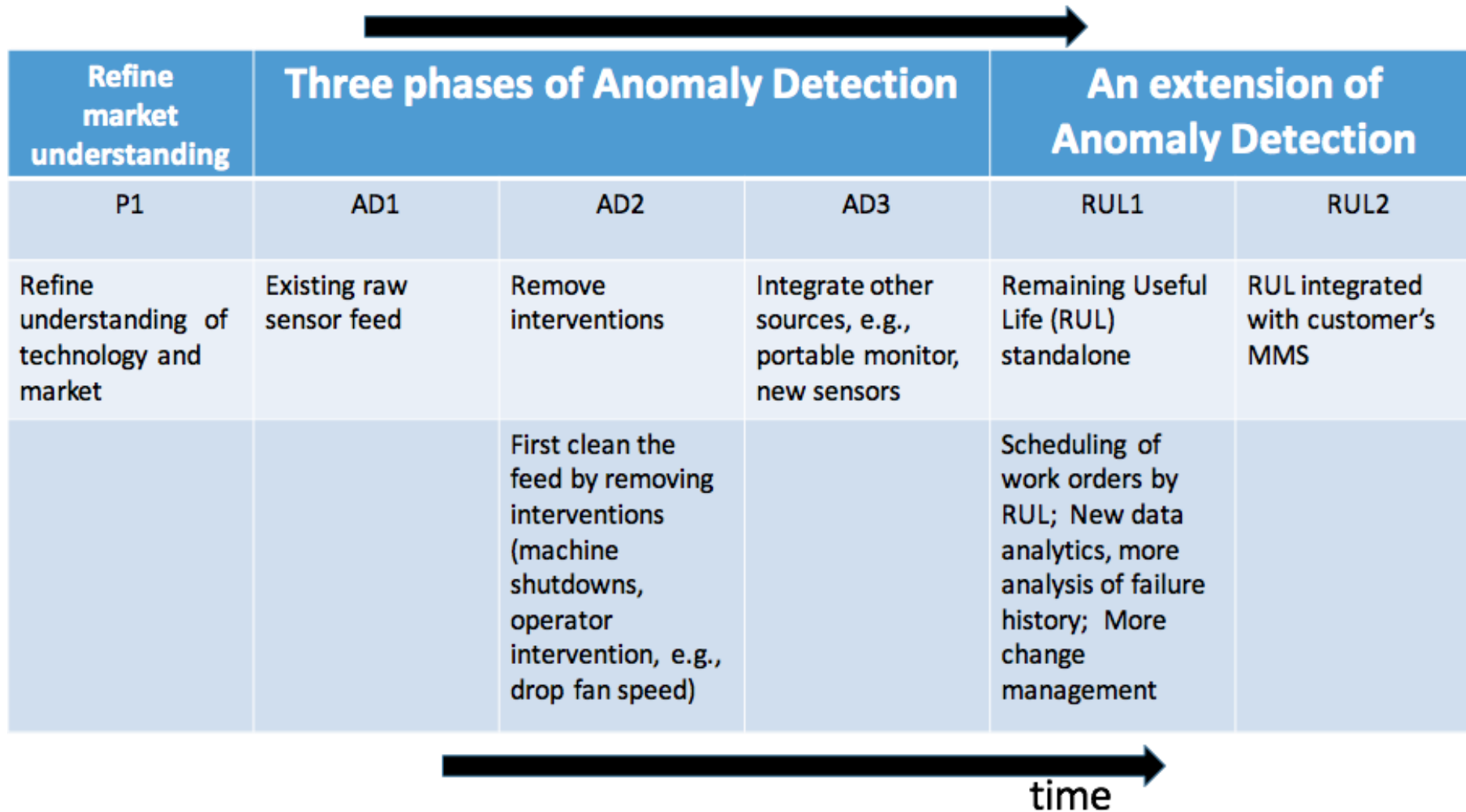


ENGAGEMENT: (STAGED) CONSULTING BUSINESS MODEL

• • • •

			Indicative costs only
Machine Intelligence Health Check, driven by customer need			\$6.5K
Further refine customer's need; Asset information study			\$30K
	Feasibility study - anomaly detection		\$125K
	Feasibility study - Remaining Useful Life		\$125K
		Design and build extended software infrastructure	\$1.2 million

EXTENDING ANOMALY DETECTION



ADDING EXTRA SENSOR

...

-- a flood coming onto market

FAG Smart Check from

www.schaeffler.de

suitable for early detection of
rolling bearing damage



Vibration motes from
Petasense

-- wireless links



Motes

Vibration Motes

From [Petasense](http://Petasense.com)



NEAR-TERM COMMERCIALISATION ACTIONS

- OZ minerals - meet Katie Hulmes *et al* and determine likelihood of consulting engagement
- Roy Hill - Simple analysis of their data (3 x gearboxes and 1 x pulley)
- Hillgrove - propose project to help them “move to AI” after reviewing Global Pumps failed project
- Engage SRA IT in partnership discussions
- Product/ service roadmap
- Paper at IMARC 2018 Melbourne 10 2018
- Review marketing help available from Austmine and METS Ignited
- Track UWA-Curtin ARC Centre “Transforming Maintenance through Data Science”
- Track BHP Maintenance Centre of Excellence

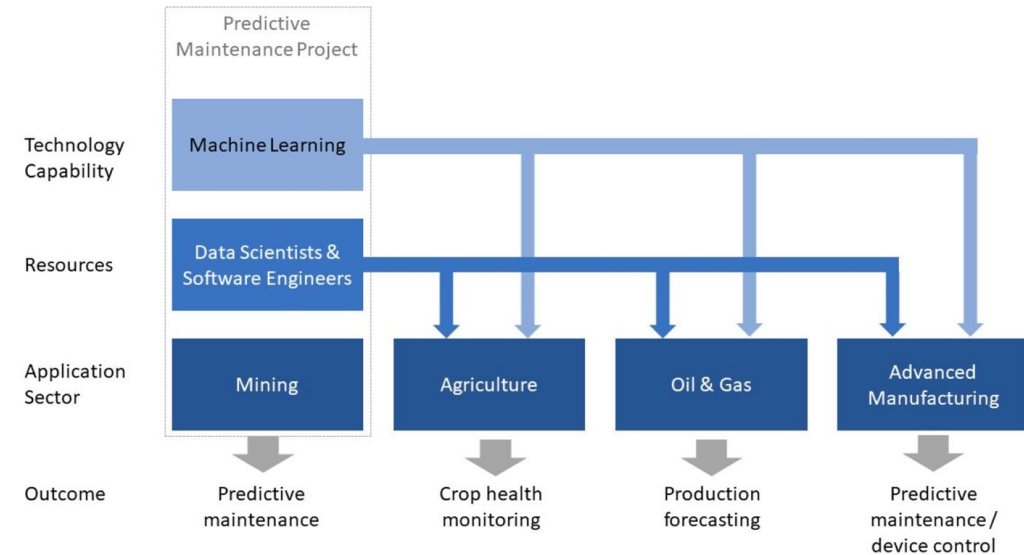
Consilium Technology

Strategic Plan

Predictive Maintenance
At Olympic Dam Copper Smelter

PDMB BENEFITS TO CONSILIUM

- Growth of Machine Intelligence capability.
 - 11 Data Sciences, incl. 6 UniSA graduates
 - Digital marketing and human interaction specialist.
- Skills and Knowledge transferred to new sectors
 - Agriculture
 - Oil and gas exploration
 - Advance manufacturing
- Consilium Growth
 - Prior: 20 employees primarily Defence
 - Post: 40 employees multi discipline

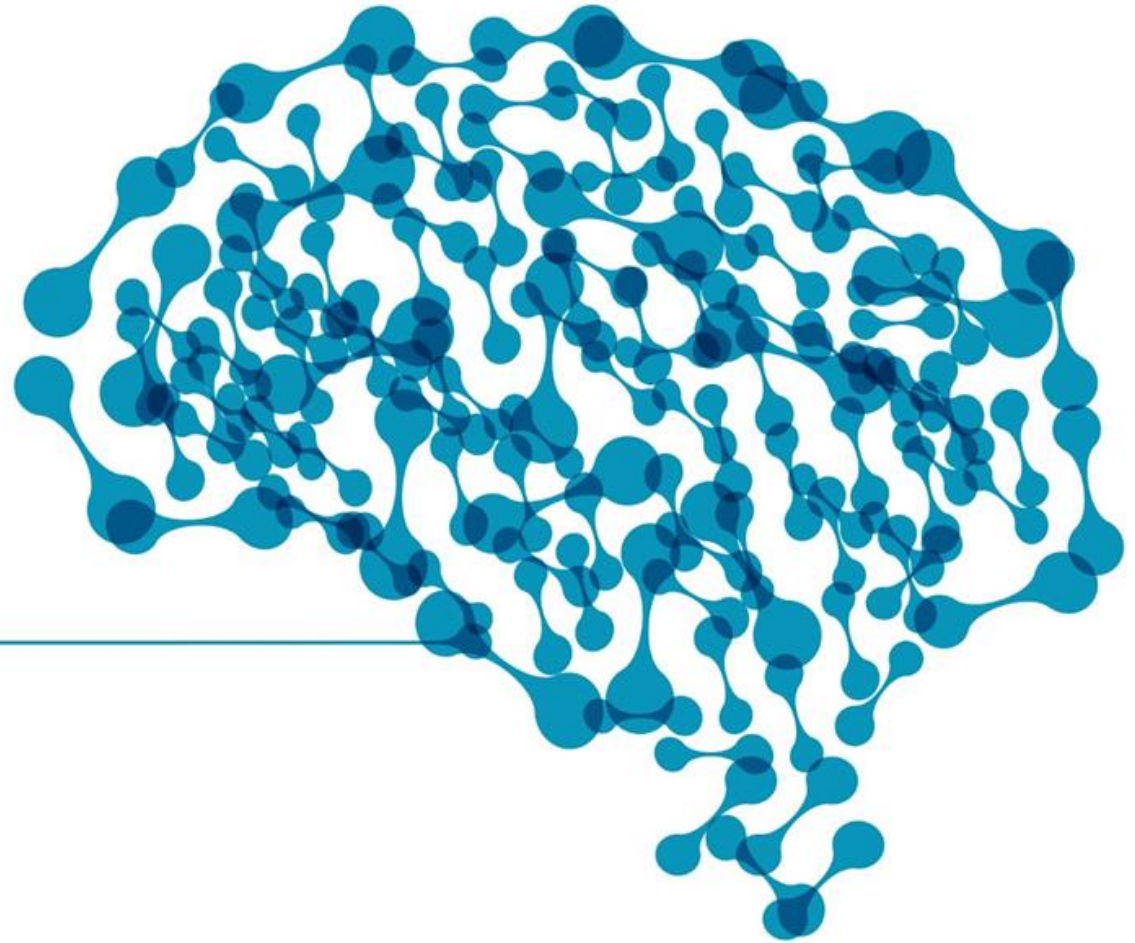


STRATEGIC PLAN



GAIA
agricultural intelligence

THANK YOU!



TIMELINE/OVERVIEW



Date	Description
Dec 2016	Project Initiation: collaborative workshop, introduction to copper smelting
Jan 2017	Data Discovery: meeting with smelter operators, develop understanding of maintenance process, formulate problem
Feb- March 2017	Preliminary data wrangling and analysis
Mar 2017	CSIRO Trainee Report
Apr - Jun 2017	Feasibility Analysis (Offgas Fan) - ML + Bayesian, Textual analysis of logs, mapping maintenance procedure
Jun 2017	Progress Report
Jul 2017	Smelter asset identification, Commercialisation planning
Aug 2017	Solution Development
Sep - Oct 2017	BHP progress report & workshop, ADT rescope
Nov 2017	ADT data identification and extraction, Anomaly detector development
Dec - Jan 2018	Label generation (data-thon), creation of ADT integrated dataset, anomaly detector development (ongoing)
Feb - Mar 2018	Anomaly detector development (ongoing), NAB integration, benchmarking
Feb - May 2018	Commercialisation planning, Final Report

Initial Off-Gas Fan Modelling

OFF-GAS FAN

Smelter Operator: Shu Chen (January 2017):

Offgas Fan Problem

“The Electric Furnace offgas fan (FA1080) impeller slowly gets build-up due to carry over of fine particles/water in the offgas. This negatively affects furnace draft control. We manage this impact by decreasing the differential pressure (or velocity) of the upstream venturi scrubber, however eventually it will reach a point that dP can not be further decreased and the fan must be cleaned and as a result the whole Smelter has to stop. We monitor the fan vibration and bearing temperatures to predict campaign life and this is currently one of determining factors of the 3 monthly Smelter shutdown.”

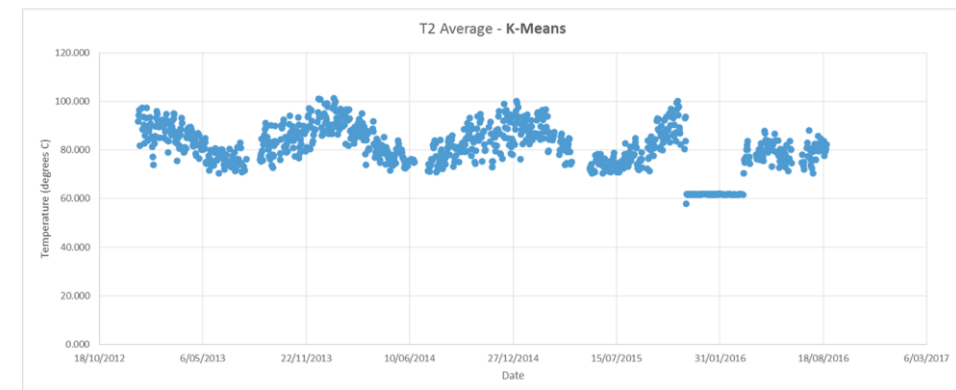
PROCESS DATA

- Process data for the FA1080 provided for the duration of 2013-2016.
 - Hourly Data, Snapshot of real time values from Citect monitoring system.
- Data consists of:
 - 3 Vibrations (mm/s)
 - 8 Motor Resistance Temperature Detectors (RTDs) (degrees C)
 - Fan Speed (%)
 - Volume Flow (Nm³/Hr)
 - Discharge Duct Temperature (degrees C)
 - Inlet Duct Pressure (mm WG)
 - Draft Control (mm WG)
 - Venturi Scrubber Differential Pressure (mm WG)

CSIRO - TRAINEE REPORT

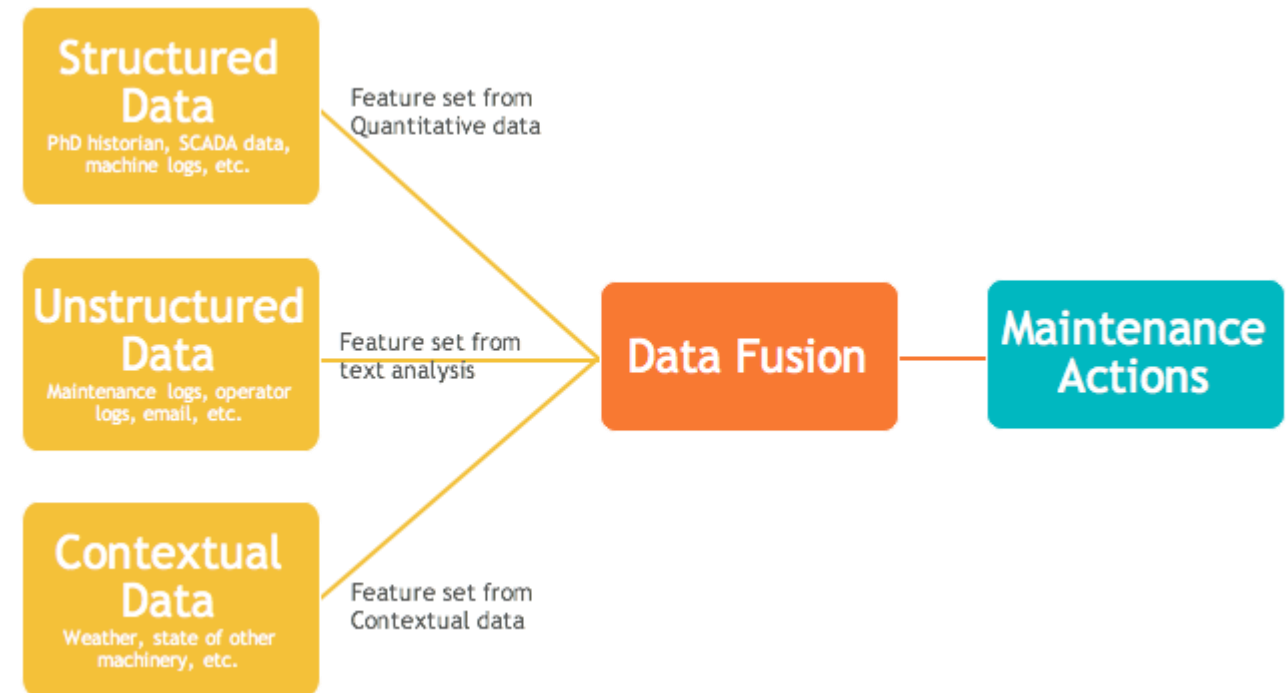
- Industrial Trainee Harry Conor Lucas
 - December - February 2016-2017
 - Literature Review
 - Offgas Fan Analysis
 - Initial Data Cleaning
 - Clustering and Seasonality
 - Data Visualisation
 - Simple ML modelling - Neural Networks - Predicting Failures
- R
 - H2O
 - Azure

Lucas, H., (2017) "CSIRO Industrial Trainee Report: Predictive Maintenance at Olympic Dam." February 2017



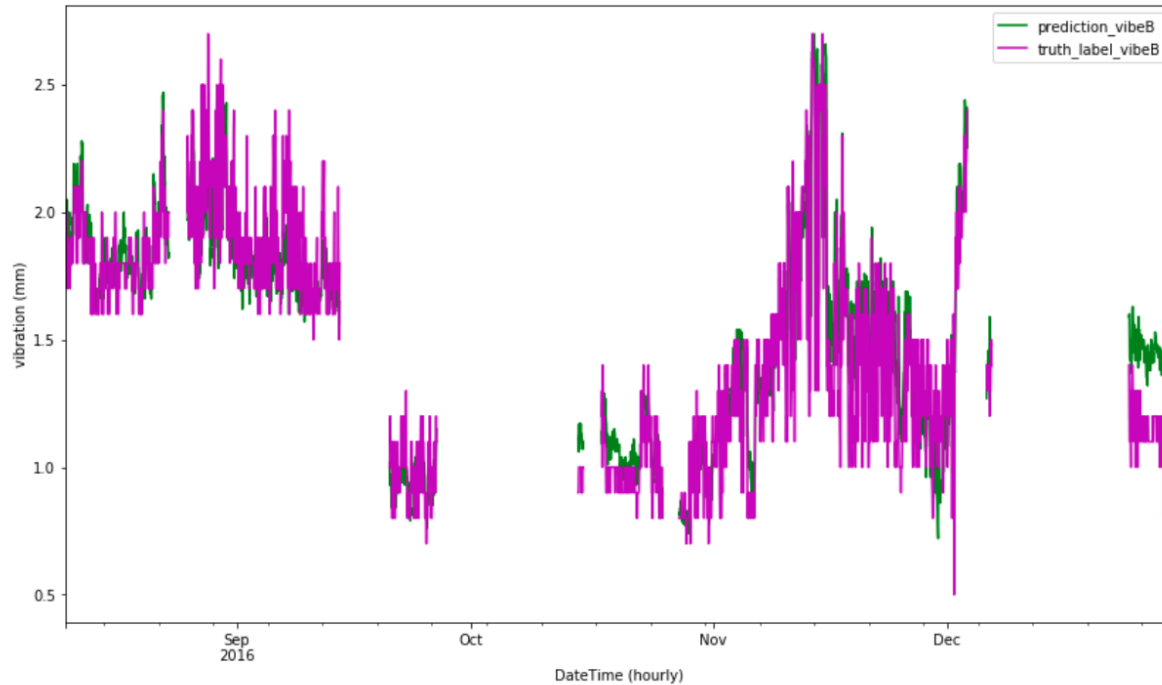
PREDICTING FAILURES / VIBRATION

- Investigation of Machine Learning and Physics Based Algorithms
 - Simple linear and nonlinear regression models
 - Relationships between sensor variables
 - Neural Network
 - NARC
 - Multi-layer perceptrons
 - Recurrent Neural Networks (LSTM)
 - Bayesian - Particle Filter
- Textual Analysis
 - Word2Vec of Notifications
 - Data61 Ampla analysis
- Initial investigation of ADT
 - N-Sigma
 - Bayesian Change Point



CSIRO-Consilium., (2017) "Predictive Maintenance Project Progress Report." June 21 2017

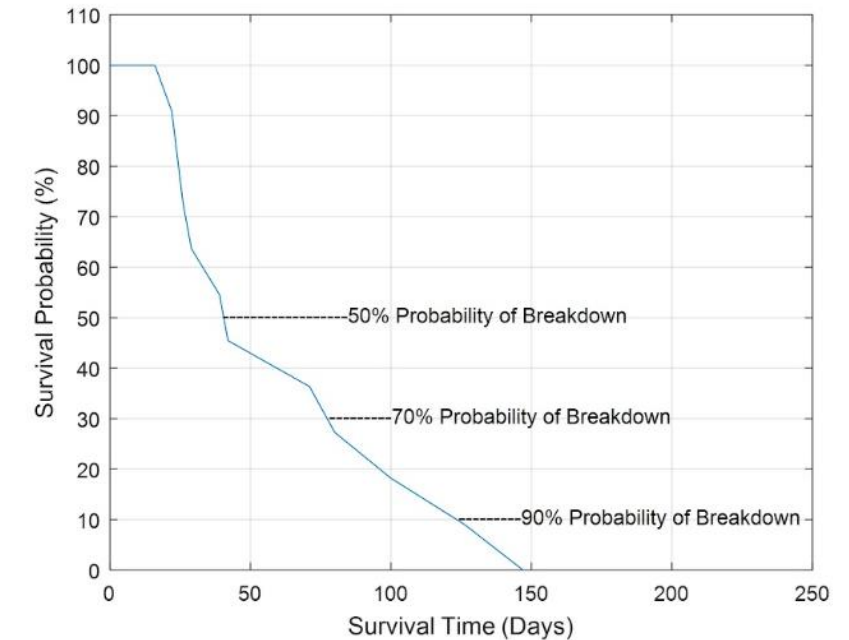
PREDICTING VIBRATIONS



LSTM

FA1080 Breakdown* Function

*Where breakdown is defined as greater than 3 mm/s vibration



NARX

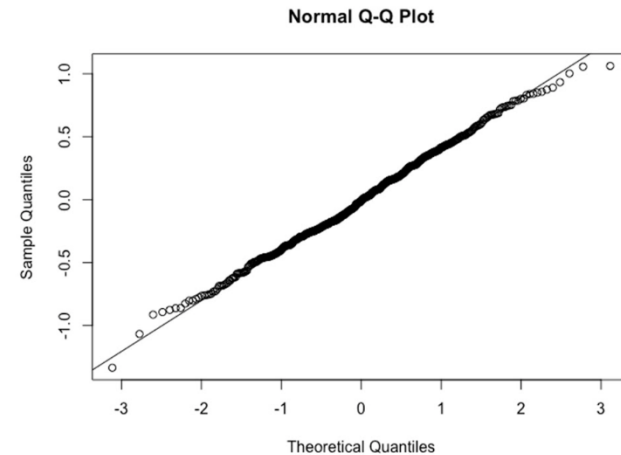
PREDICTING VIBRATIONS



Modelling



- Model: $\text{glm}(\log(\text{Mean Vib A}) \sim \text{EF Total Slag} + \text{Var Vib A} + \text{Day} + \text{Day} * (\cos(2 * \pi * y / 365.25) + \sin(2 * \pi * y / 365.25)) + \text{Shift Term Frequency})$



Shift Terms Included:

- fa1080
- start
- trip
- work
- inspect
- back
- complet
- issu
- level
- check
- issu
- level
- isol
- chang
- dust
- blister
- good
- put

Particle Filter Textual Analysis

CHALLENGES

- Lack of documented “definitive” failure labels.
 - Asset rarely run to full failure?
 - Proxies?
- Identifying and classifying “Events”
 - Rare
 - Unique
 - Different in scale
 - Cause flow on effects or clump together
- Sensor data
 - High level of operator interaction
 - Non uniform sensor configuration
 - Vibration only used for a few rotational assets

Data resolution vs Hand Held Analyser