Artificial Intelligence in Manufacturing

Predicting, diagnosing and optimizing industrial assets and operations

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Watson IoT

Categorizing AI definitions

Thought and Behavior

Thinking Humanly
"[the automation of] activities that we associate with human thinking, activities such as decision making, problem solving, learning…" (Belman, 1978)

Acting Humanly
"The art of creating machines that perform functions that require intelligence when performed by people" (Kurzweil, 1990)

Thinking Rationally
"The study of the computations that make it possible to perceive, reason, act" (Winston, 1992)

Acting Rationally
"AI … is concerned with intelligent behavior in artifacts" (Nilsson, 1998)

IBM: "AI is the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem solving."
Examples of technologies that enable AI to solve business problems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

IoT for manufacturing is about how IoT helps to drive more efficiency in your “people, process and things”

Intelligent assets and equipment

Intelligent assets and equipment utilizes IoT and cognitive capabilities to sense, communicate and self-diagnose issues so they can optimize their performance and reduce unnecessary downtime

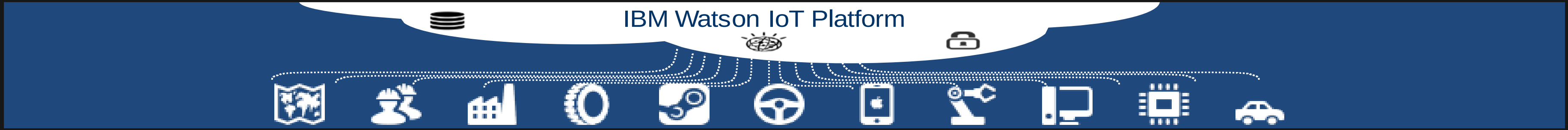
Cognitive production processes

Cognitive operations and processes bring more certainty to business by analyzing a variety of information from workflows, context and environment to drive quality, enhance operations and decision-making.

Resource optimization, knowledge engineering

Utilize IoT and cognitive insight to optimize resources (worker, energy, expertise) using geolocation data, individual data, usage data and environmental conditions along with analytics.

34%	25%	8%
Decrease in equipment downtime at major global auto manufacturer	Increase in overall productivity at major European automaker	Annual saving in energy cost at IBM facilities



Assets and Equipment

Asset intensive organizations need optimize their maintenance strategy helping them to remain competitive

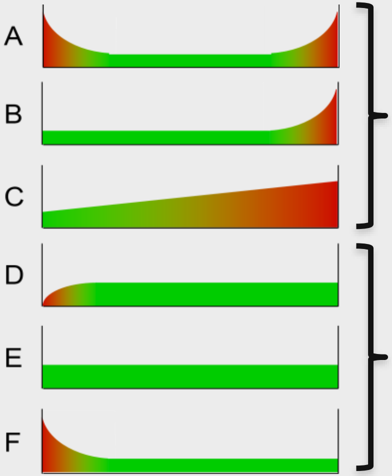
30% Maintenance activities carried out too frequently

45% All maintenance efforts are ineffective

40% Scheduled maintenance costs are spent on assets with negligible effect on uptime

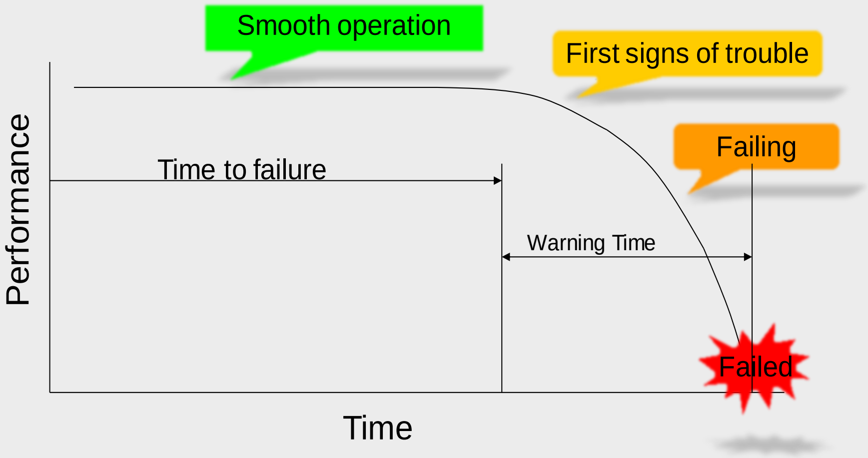
Sources: 1. Oniqua Enterprise Analytics, Reducing the Cost of Preventative Maintenance
2. T.A. Cook, Maintenance Efficiency Report 2013, August 2013

Fundamental ‘Truths’ about Asset Management Today



Approximately 11% of components of a complex asset fail over time

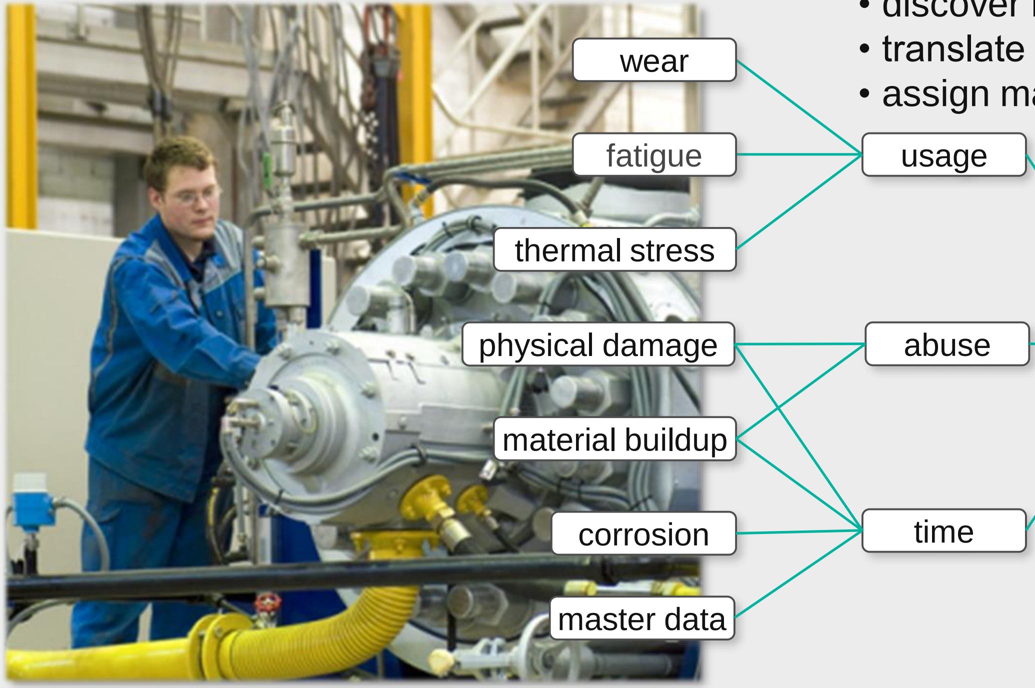
89% fail randomly over time

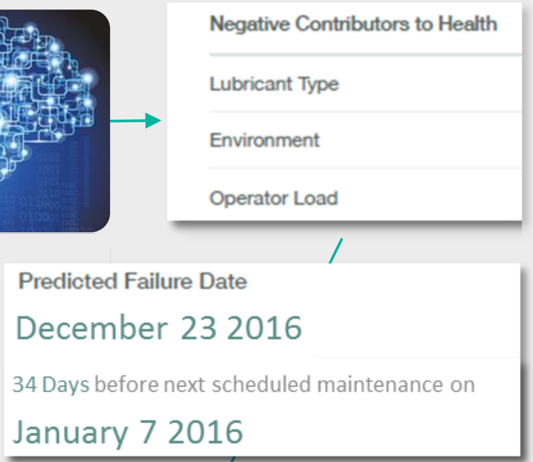


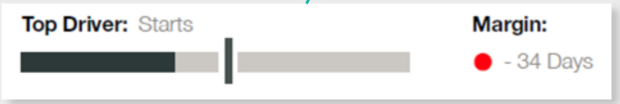
Addressing the 89% random failures with a combination of asset priorities data, operations data, maintenance data supported by analytics is key to being a leader in this challenge.

Machine learning automatically analyzes variables to correlate degree of use/abuse with failure

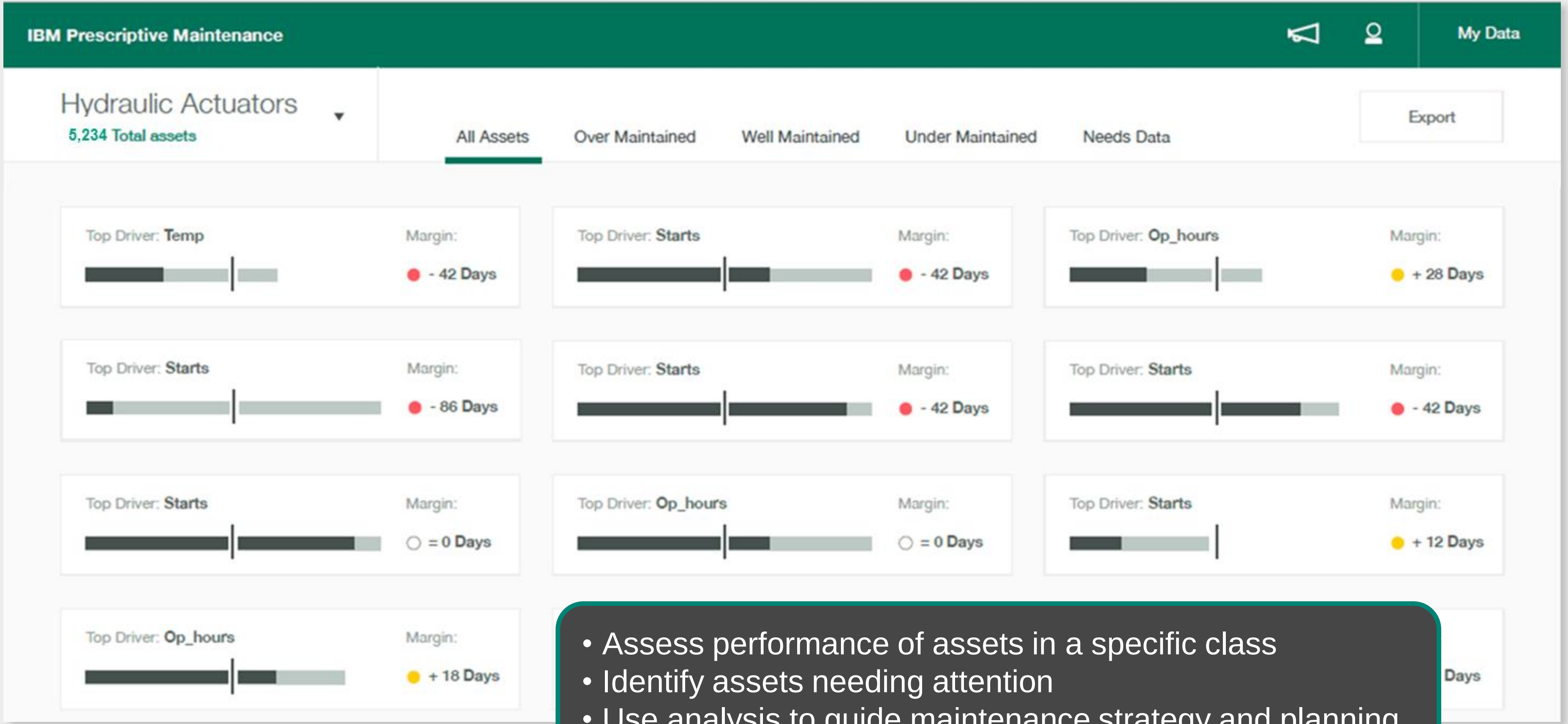
- identify metrics that are indicative of equipment failure
- discover how usage patterns influence failure patterns
- translate metrics into a “remaining days before failure”
- assign maintenance classification – over/under/well





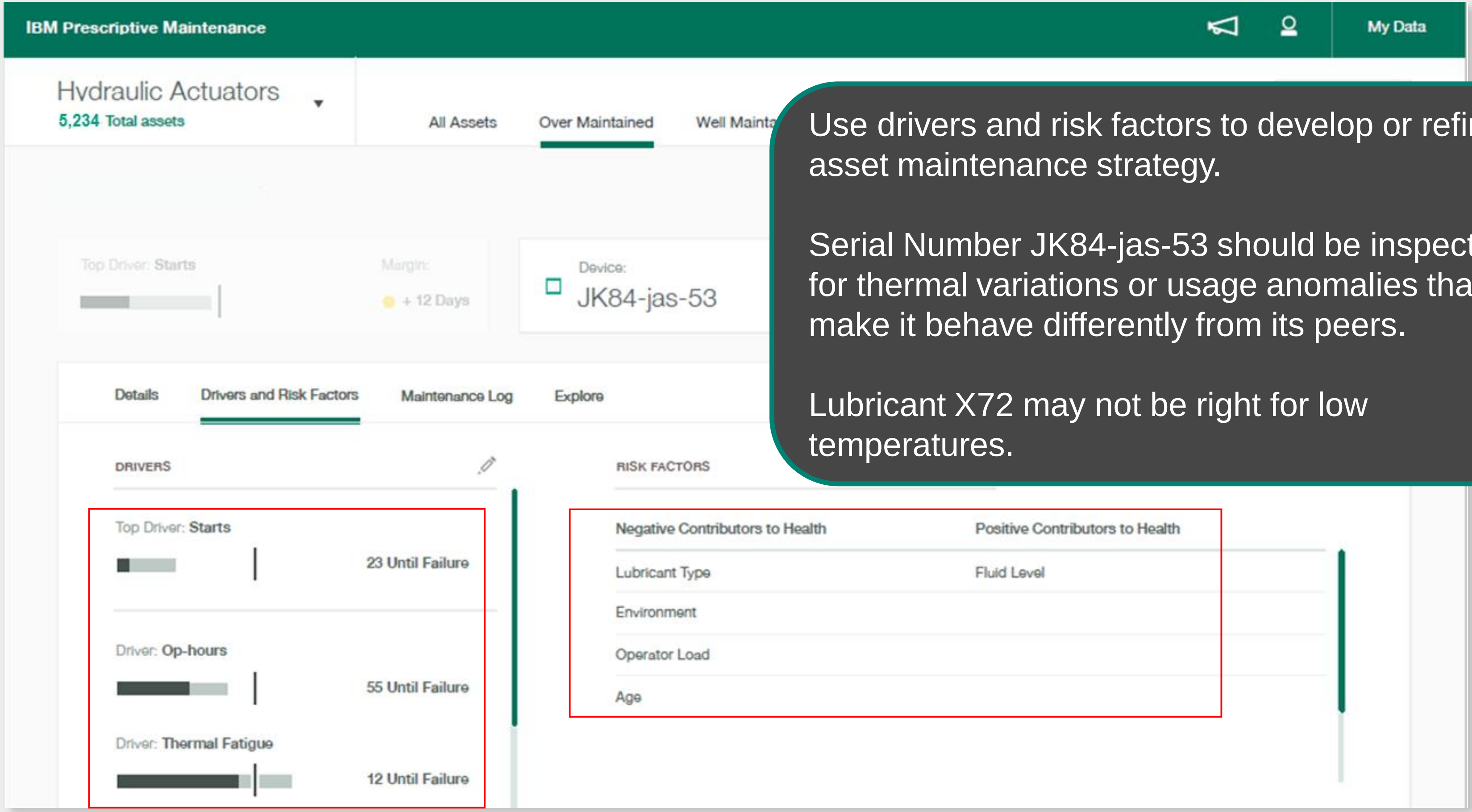


Easily assess maintenance status of an asset class



- Assess performance of assets in a specific class
- Identify assets needing attention
- Use analysis to guide maintenance strategy and planning

Machine learning identifies drivers and risk factors that influence asset health



Use drivers and risk factors to develop or refine asset maintenance strategy.

Serial Number JK84-jas-53 should be inspected for thermal variations or usage anomalies that make it behave differently from its peers.

Lubricant X72 may not be right for low temperatures.

Jet Engine Manufacturer: avoid costly AOG events

- ✓ 97% accuracy in ability to predict delays and cancellations within 12 weeks
- ✓ 97% accuracy in ability to predict an in-flight shutdown within a year
- ✓ avoid millions of dollars in costs associated with grounded planes.

Use engine data obtained from various databases and sensors to predict and proactively address engine issues.

Analytics platform creates predictive models that alert the manufacturer to impending engine events. These alerts, and a dashboard visualization of engine-fleet health and risk status, enable the company to take proactive measures such as ordering and arranging preventive maintenance.

Prediction use cases

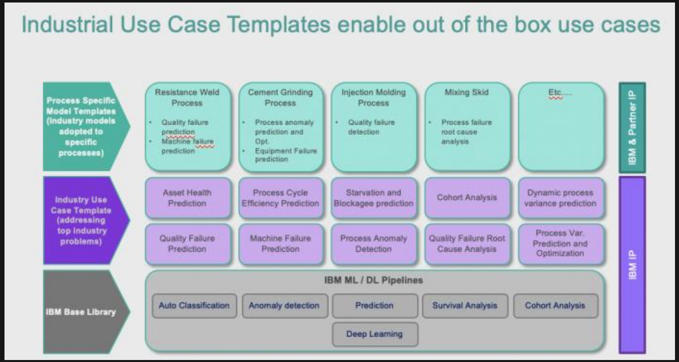
Quality Failure Prediction

Equipment Failure Prediction

Process Anomaly Detection

Process Variability Prediction and Optimization

Process Failure Root Cause Analysis



Example 1: Leak Detection

Example 2: Damage Simulation

Example 3: Simple Anomaly Model

Example 4: Automated Multi-mode Anomaly

Example 5: Automated Equipment Outlier Detection

Example 6: Pre-fail State Detection

Example 7: Hybrid Condition Monitoring / Survival Analysis

Example 7b: Pure Condition Monitoring

Example 7c: Predicting Failure in a fixed time interval

Example 8: Vibration Analysis Part 1: Explore

Example 8: Vibration Analysis Part 2: Model

Example 9: Sequence Analysis

Example 10: Selecting the best scheduling maintenance window

Example 11: Predictive Maintenance for Sporadically used Assets

Example 11: Predictive Maintenance for Sporadically used Assets

Example 12: Adjusting workload to fit a maintenance schedule

Example 13: Diagnosing Equipment Issues

Increase yield of your manufacturing operations and processes

- ✓ 25% increase in overall productivity of cylinder-head line
- ✓ 50% reduction in time required to achieve process target levels
- ✓ 100% payback achieved within 2 years

A large European automaker worked with IBM IoT to analyze more than 500 performance variables using predictive models to identify specific parts of the production line that needed adjustment. Historical and real-time manufacturing variables including machine setting, material temperature and equipment maintenance activities all contributed to prediction engine for decision support

Production processes

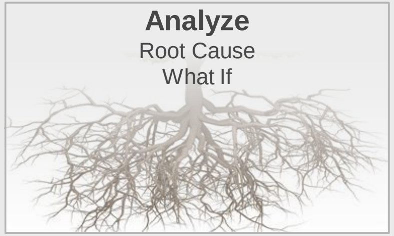
Production Losses Impact Production Performance

Achieve Performance to Potential

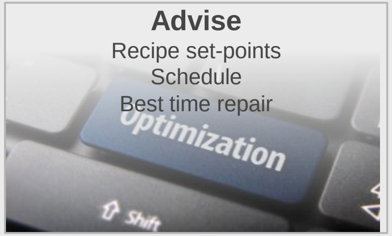
Prescribe Best Action

Predict & Pinpoint Production Losses

Maximize
Throughput
Yield
Eliminate
Waste

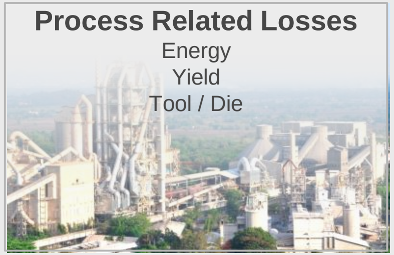


Analyze
Root Cause
What If



Advise
Recipe set-points
Schedule
Best time repair

Equipment Related Losses
Availability
Performance
Quality



Process Related Losses
Energy
Yield
Tool / Die

Productivity Related Losses
Material Availability
Labor
Line Balance

Identify Losses, Eliminate Waste, Increase throughput and Optimize Production

Industrial Analytical Model Templates enable out of the box use cases

Process Specific Model Templates (Industry models adopted to specific processes)

Resistance Weld Process
- Quality failure prediction
- Machine failure prediction

Cement Grinding Process
- Process anomaly prediction and Opt.
- Equipment Failure prediction

Injection Molding Process
- Quality failure detection

Mixing Skid
- Process failure root cause analysis

Industry Analytical Model Template (addressing top industry problems)

- Asset Health Prediction
- Process Cycle Efficiency Prediction
- Starvation and Blockagee prediction
- Cohort Analysis
- Dynamic process variance prediction
- Quality Failure Prediction
- Machine Failure Prediction
- Process Anomaly Detection
- Quality Failure Root Cause Analysis
- Process Var. Prediction and Optimization

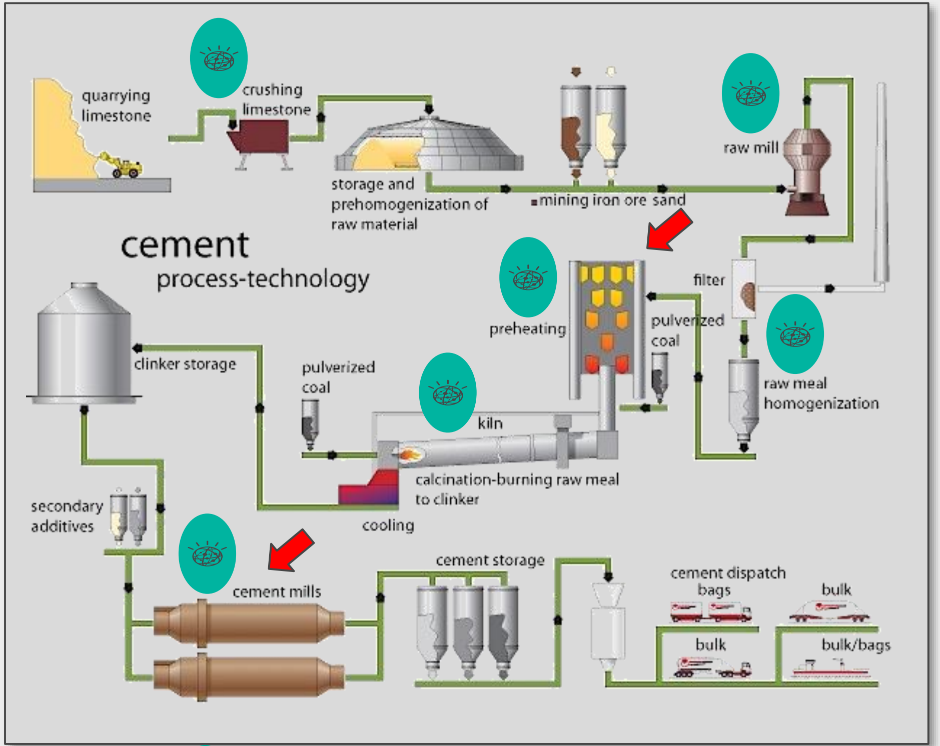
IBM Base Library

IBM ML / DL Pipelines

- Auto Classification
- Anomaly detection
- Prediction
- Survival Analysis
- Cohort Analysis
- Deep Learning

Cement Production

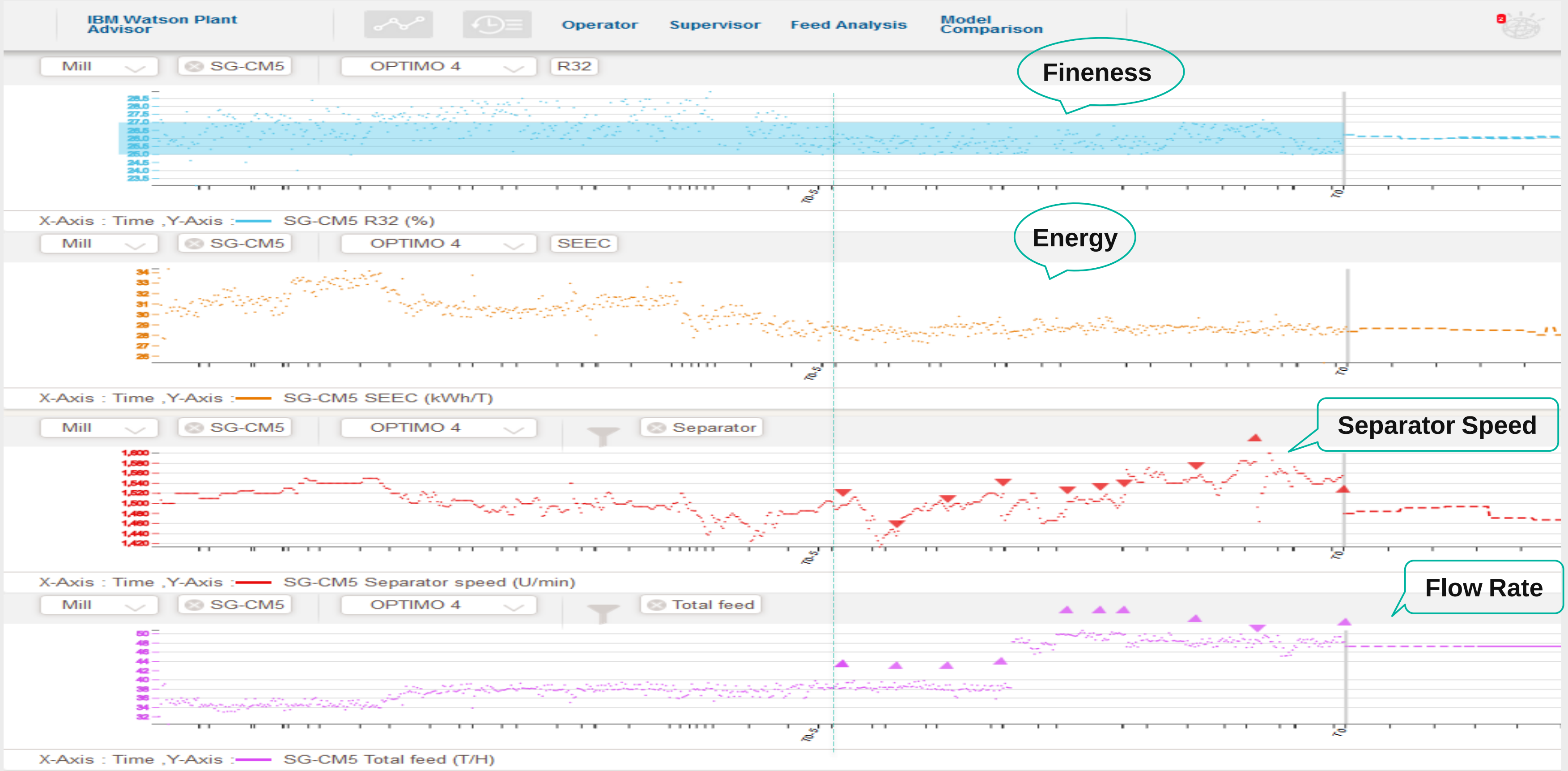
- High energy intensive process
- 40% variability from best to worst
- Inefficient operations are only identified after the fact, affecting profitability.
- Hard to understand complex multivariable correlations
- Hard to understand changes in plant behavior over time
- Few experts in the headquarters
- Hard to convey experience to novice operators / process engineers in a structured manner
- Knowledge is lost when an experienced plant engineer leaves the company
- Many plants around the globe



Potential Plant Advisor applications

What if you could make **every** operator perform like your **best** operator?

Cement Grinding Mill Optimization Results



Variables

Target Variables

Manipulated Variables

Observed Variables

Unit	Explanation
t	Total cemnt production of CM7
kWh	Power Consumption
kWh/t	**Specific power consumption of CM7**
KW	Mill main motor power (HA1+HA2)
t/h	Total mill fresh feed (Sum of all feeders)
t/h	**Clinker feed. Main control variable**
t/h	Gypsum feed
t/h	Limestone feed
t/h	Additives feed
t/h	Clinker dust feed
ML/MIN	Grinding aid dosing
U/MIN	**Separator speed adapted by R32**
%	Swirl blade pitch
cm2/g	Blaine (LIMS)
	Residue 32 mu sieve (LIMS)
	Reject flow
hPa	Mill inlet under- pressure (Indicator of mill air flow)
hPa	Mill Outlet under-pressure (Indicator of mill air flow)
hPa	Differential Pressure over filter
hPa	Differential Pressure over filter (Indicator of separator air flow)
° C	Temperature cement (Air temp through mill used for cooling)
° C	Clinker temperature
GRD	Separator filter exit gas temperature that should be < ~ 100° C
° C	Cement cooling air temp by mill and separator air flow (should be < ~ 90 deg)
A	Bucket elevator current (Indicator for mill filling degree)
A	Separator fan current (Indicator for Separator air flow)
A	mill fan current (Indicator for mill air flow)

KPIs

Controllable

Quality

Machine Learning Pipeline

Data definition

Control
Sum. fresh feed
Grinding aid
Separator speed

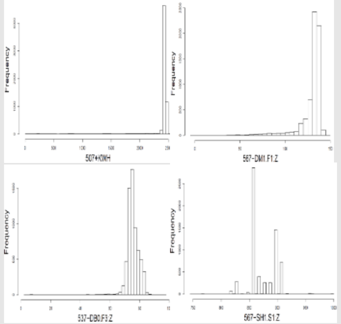
Observed
Mill Temperature
Clinker Temp.
Separator Temp.
Reject flow
Sep. fan current
Mill fan current

Target
Electricity consumption
Cement fineness

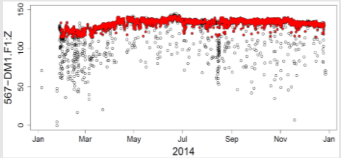
Production Optimization

data pre-processing

Unsupervised learning

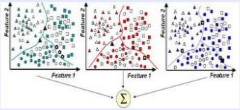


Data filtering

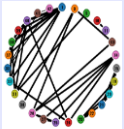


ML libraries

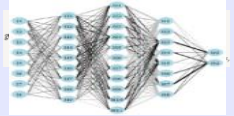
Ensemble learning



Sparse learning



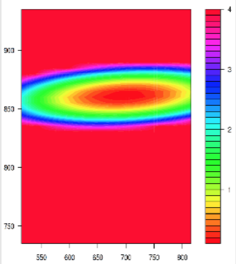
Function shape learning



Optimization

$$J(\boldsymbol{Y};\boldsymbol{x}) = \lambda_1 \|Q(\boldsymbol{Y};\boldsymbol{x}) - Q^T\|_2^2 + \lambda_2 \left(Rej(\boldsymbol{Y};\boldsymbol{x}) + \sum_{i=1}^{m} \alpha_i Y_i \right) + \sum_{i=1}^{m} \gamma_i \|Y_i - Y_i^*\|_2^2$$

$$\arg\min_{\boldsymbol{Y} \in \mathbb{R}^m} E[J(\boldsymbol{Y};\boldsymbol{x})]$$



Knowledge engineering

Increase worker productivity and expertise

- ✓ Collated 30+ years of engineering expertise
- ✓ Reduced onboarding and training time of new engineers
- ✓ Faster resolution of problems and increase productivity of workforce

Engineers at Woodside are training Watson to collate 30+ years of engineering experience in managing liquid gas facilities to create a cognitive advisory service to help employees across the organization resolve problems faster, improve process flow and achieve better operational outcomes.

Cognitive diagnosis

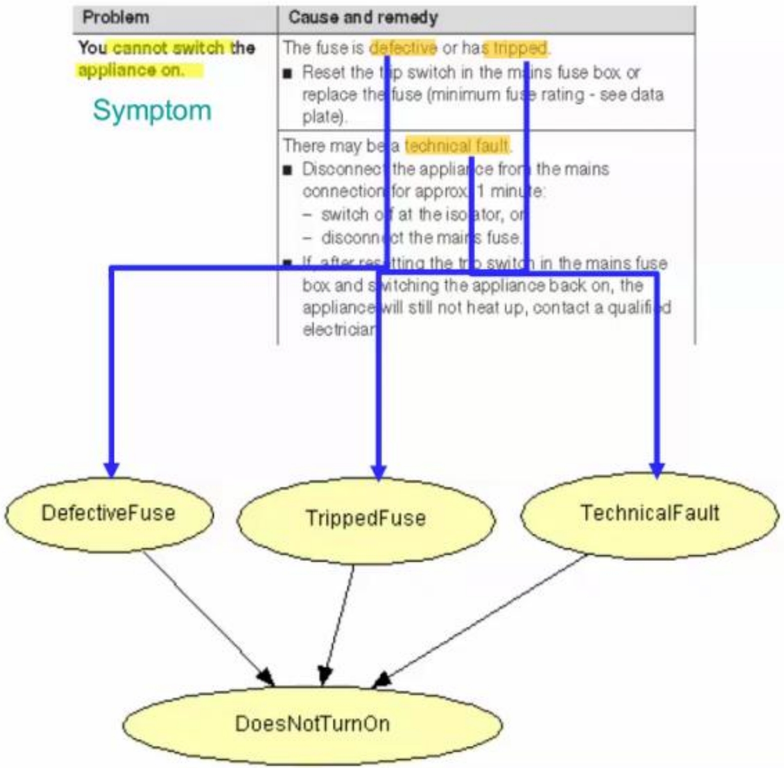
Suggests the most likely **causes** for a given set of **symptoms**

Complements the Discovery-based intelligent querying capability

Particularly effective in complex cases involving multiple symptoms caused by multiple problems

Learns and improve based on usage in the field

Client Case Study: Germany-based OEM



Client: German-based manufacturer of high-end domestic appliances and commercial equipment

Business Challenge:

- Reduce unnecessary replacement of parts. Additional goals/Metrics of interest:
- Time spent by technicians
- First-fix rate

Solution:

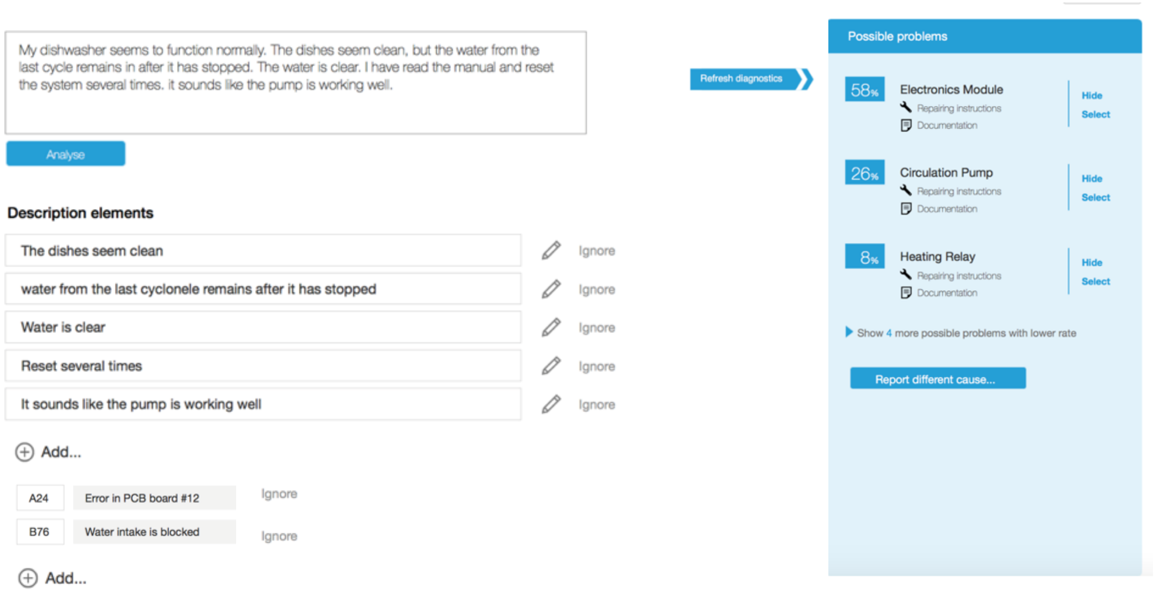
- Two equipment types: dishwasher and steam oven
- Used diagnosis troubleshooting capability to help technicians diagnose the correct problem on malfunctioning equipment and provide recommendations

Business Value:

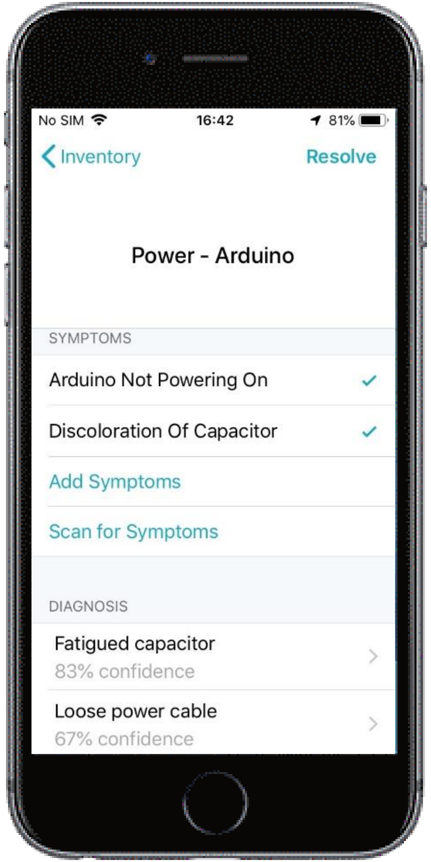
- ~30% reduction for the electronic module parts replaced in the dishwasher
- Initial model for steam oven results: Watson top recommendation correct ~78% of the time

Experience

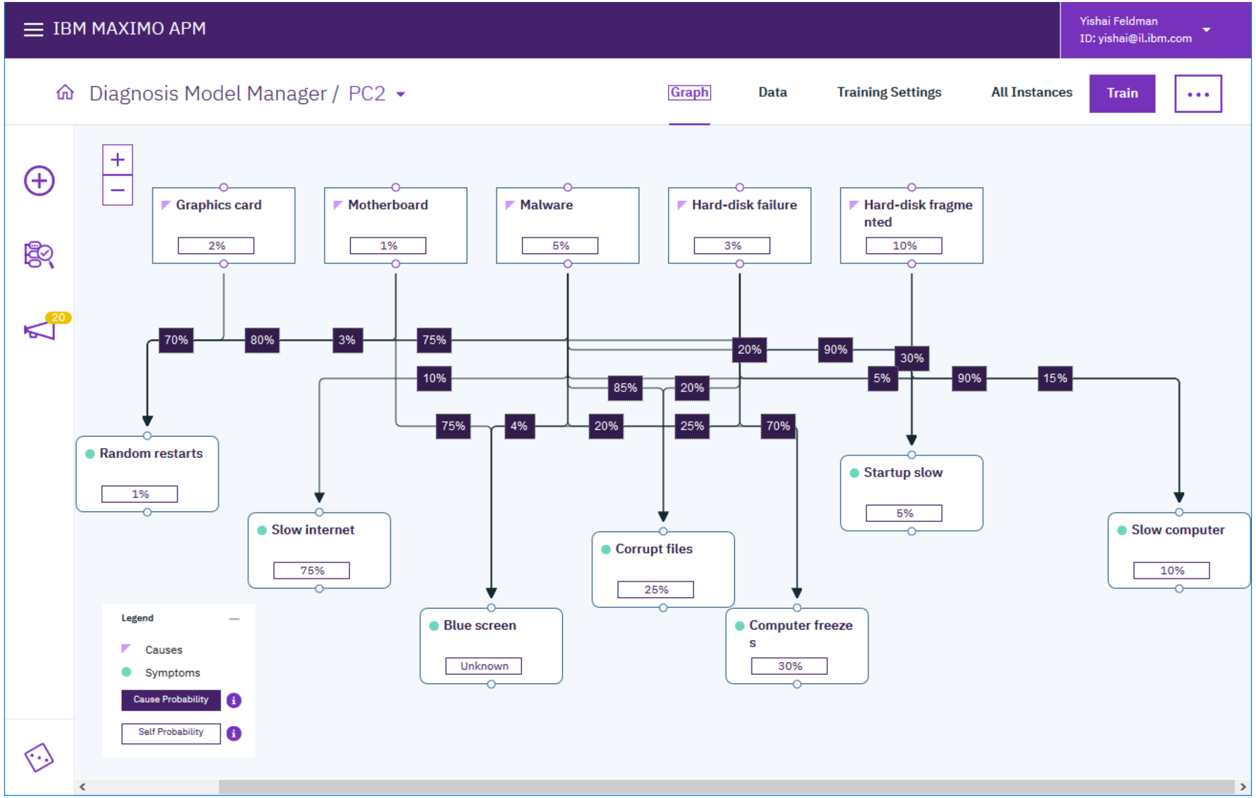
Fifteen-month engagement with a large appliance manufacturer

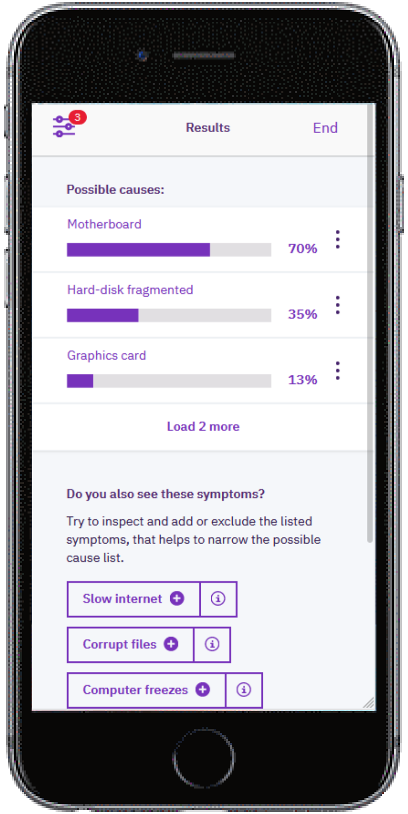


Three-month PoC with Coca Cola (presented at Think 2018)



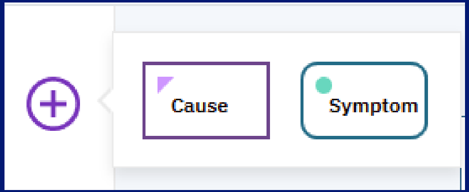
Cognitive Diagnosis Model Manager and Technician App



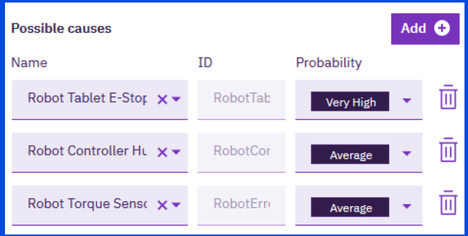


Developing a diagnosis model

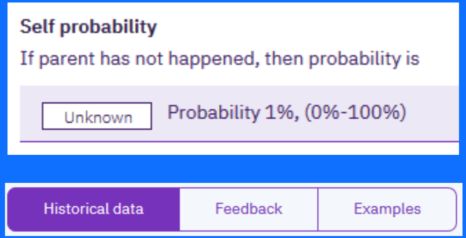
Create symptoms and causes



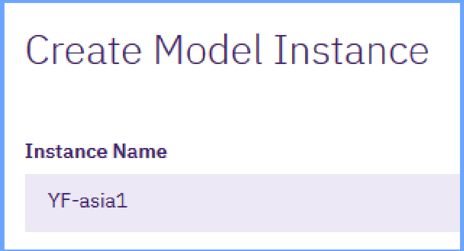
Connect causes to symptoms they can manifest



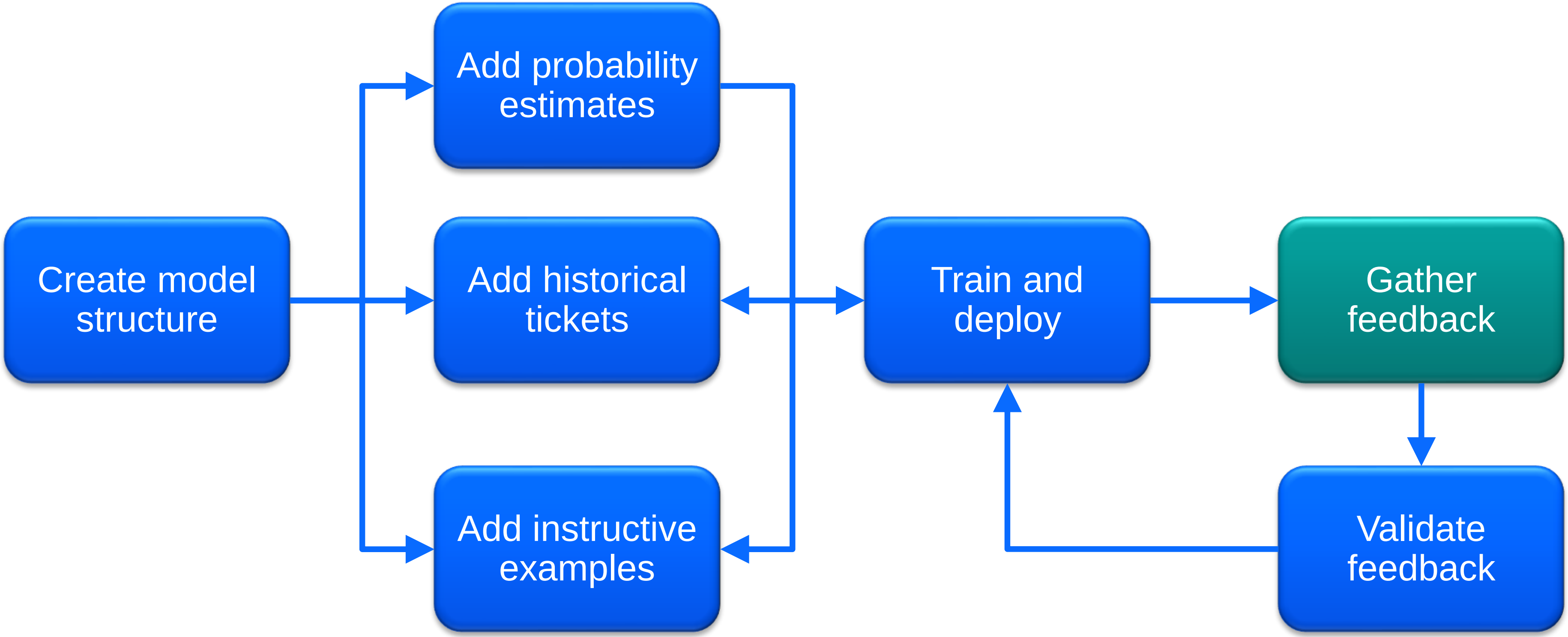
Populate model with probabilities



Train model



Improving accuracy



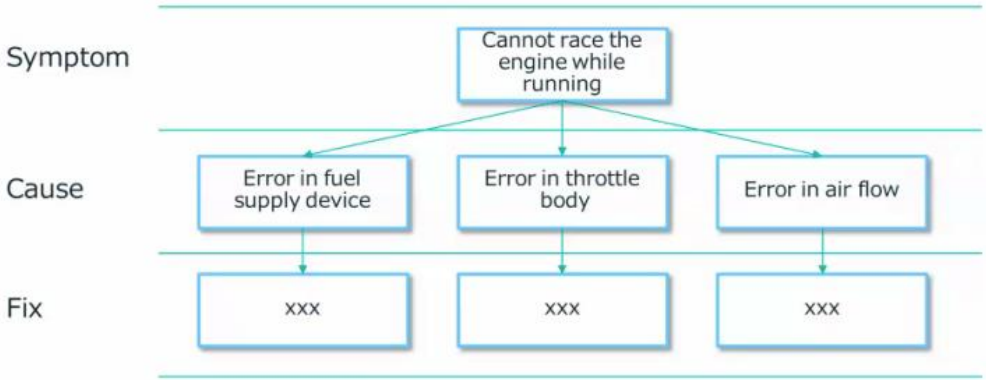
EMA Diagnosis

More advanced repair and troubleshooting capabilities than standalone Watson components

Functional value of problem diagnosis capabilities:

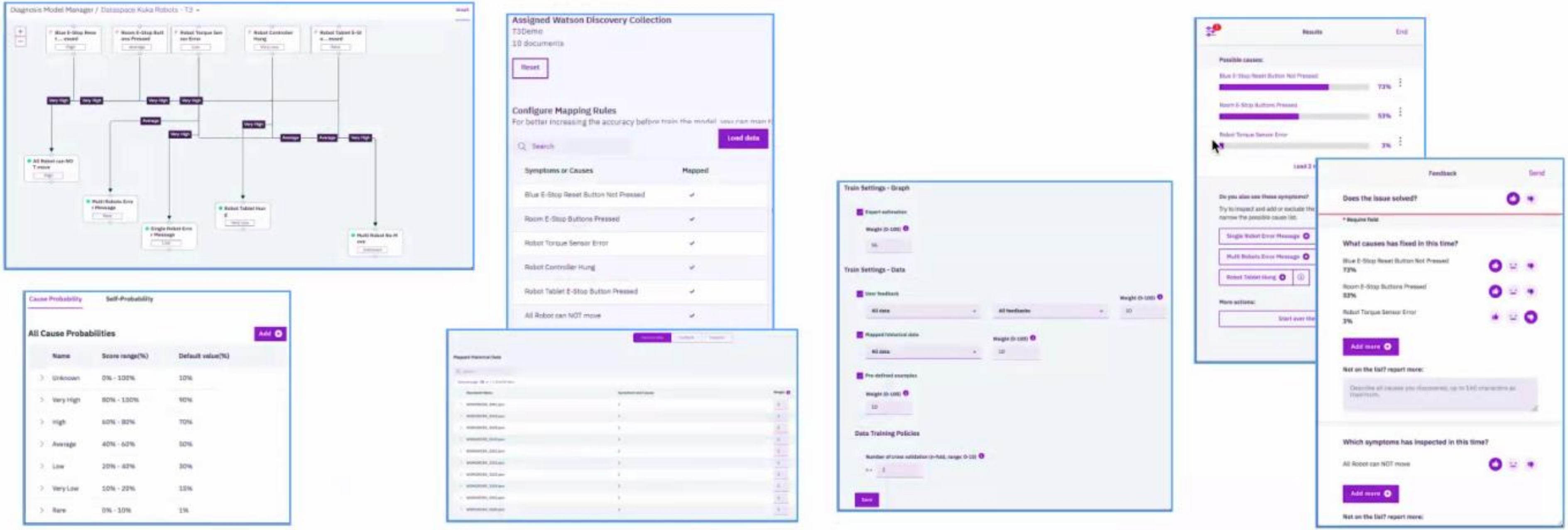
- Your clients have existing maintenance processes in place:
  - Problem Cause Remedy
  - Custom engineering processes such as Failure Modes and Effects Analyses (FMEA) or Root Cause Failure Analyses (RCFA)
  - EMA can capture these existing maintenance processes

- Custom diagnostic trees can be used



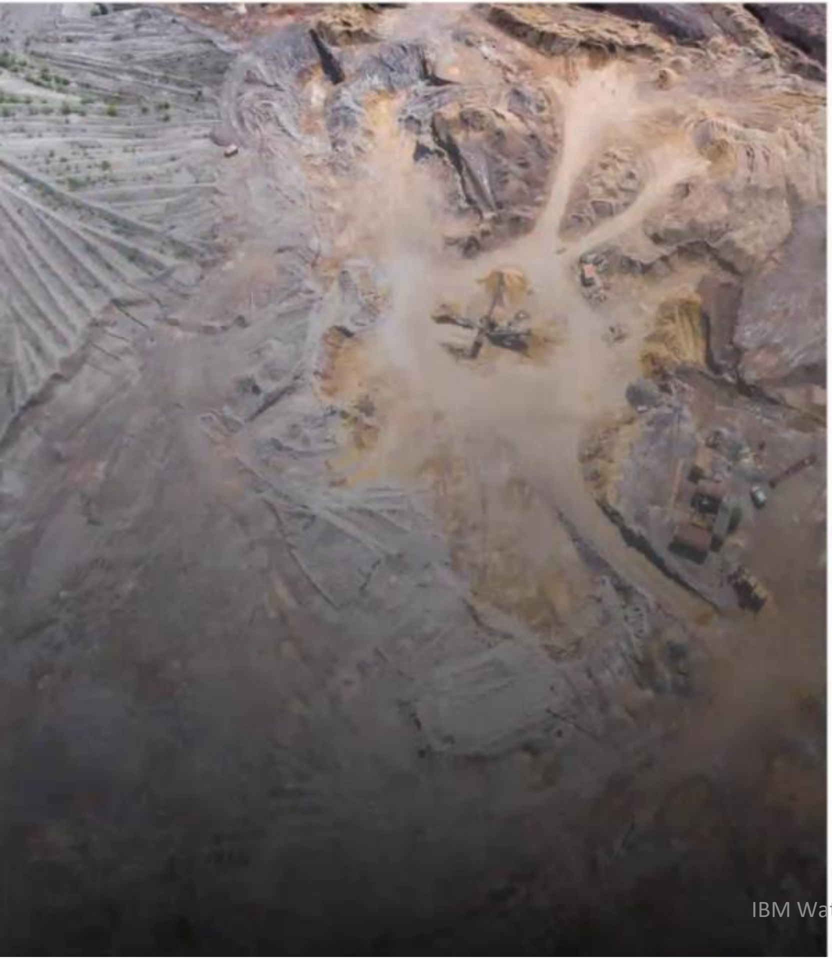
EMA Diagnosis

End-to-end workflow



Create/Update Diagnosis Model → Load Data for Model Training → Train Model → Run Diagnosis

Woodside Energy (Oil and Gas)



Client: Australia's largest independent oil and gas company

Business Challenge:

- Aging workforce and heavy reliance on historical context and procedural information.
- Employees spent 80% of their time researching problems and 20% fixing it. Need for easy access to detailed answers to highly industry specific questions in remote locations
- Access to prior project documentation to incorporate valuable insights into current projects

Solution:

- Watson absorbed over 600,000 pages of documentation, from reports to correspondence regarding drilling equipment
- Client's employees have the ability to obtain immediate access to years of knowledge and experience to deliver and build enhanced products based on prior work
- Increased knowledge about prior projects results in the application of best practices and more satisfied customers

Business Value: Time spent on researching reduced by 75% which equates to US$10 million-worth of time savings.
Safety procedures are shared with all employees, including new hires

Video trailer link [here]

Watson IoT™