PHM Society 2021 Conference Tutorial

Methodology and Case Studies for Fielding PHM Systems – Successes, Challenges, and Lessons Learned

Presenter: David Siegel

PHM SOCIETY 2021 CONFERENCE TUTORIAL
OVERVIEW

- Overview
- Challenges in Fielded PHM Systems
- PHM Development and Deployment

Industrial Case Studies

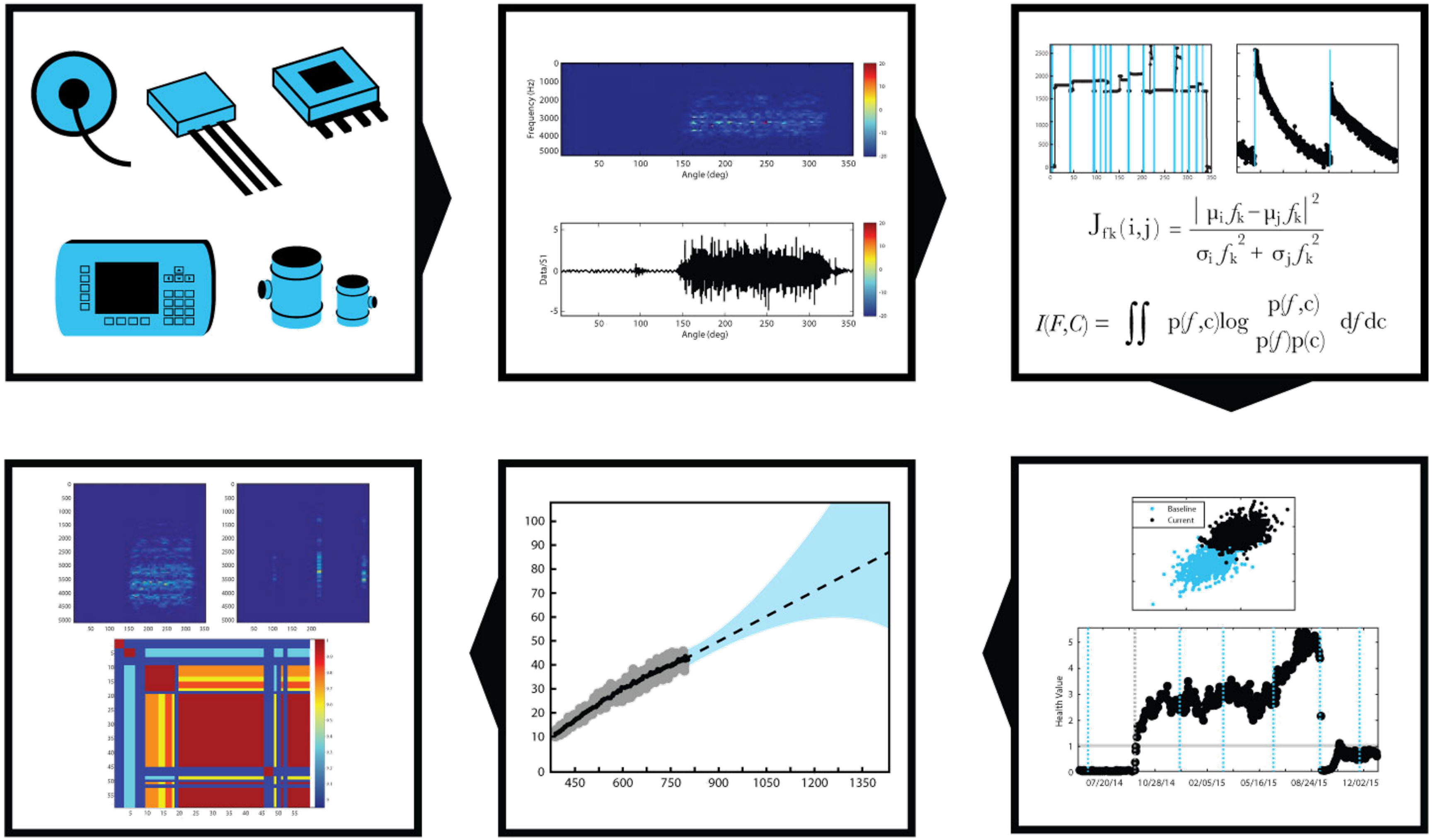
  - Manufacturing
  - Heavy Industry
  - Aerospace

- New Developments and Concluding Remarks

Overview

DATA-DRIVEN PROGNOSTICS AND HEALTH MANAGEMENT DEVELOPMENT

Data Collection | **Signal Processing** | **Feature Extraction**



Fault Diagnosis | **Trending / Prediction** | **Health Assessment**

PHM INDUSTRIES (PAST PROJECTS / USE CASES)

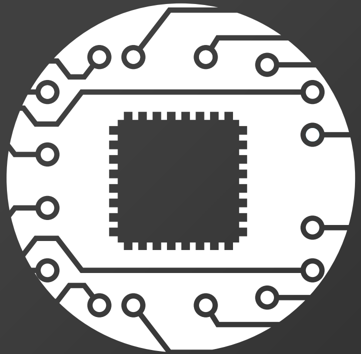
Manufacturing

Transportation

Aerospace

Energy

Cargo & Logistics



Semiconductor Manufacturing

Industrial Vehicles

Industrial Equipment

Raw Materials Manufacturing

SUCCESS STORIES

MANUFACTURING SECTOR

ORGANIZATION	DESCRIPTION	BENEFIT
IMS Center[1]	The IMS Center has generated over $847.6M of economic impact to its members with a benefit cost ratio of 238:1	$847.6m
Toyota	Data-Driven Surge Map Models and Surge Detection for Centrifugal Air Compressors	$6.5m when expanded to the full production facility
Appliance Manufacturer	Autonomous Production Anomaly Detection Agent by Data Mining Methods	Improvements in product quality and millions in savings from downtime reduction
Aerospace Manufacturer	Machine Tool Health Assessment by Fixed Cycle Feature Test	Multiple assets in two factories were monitored and severe machine breakdown was detected two weeks in advance

SUCCESS STORIES

ADDITIONAL INDUSTRIES

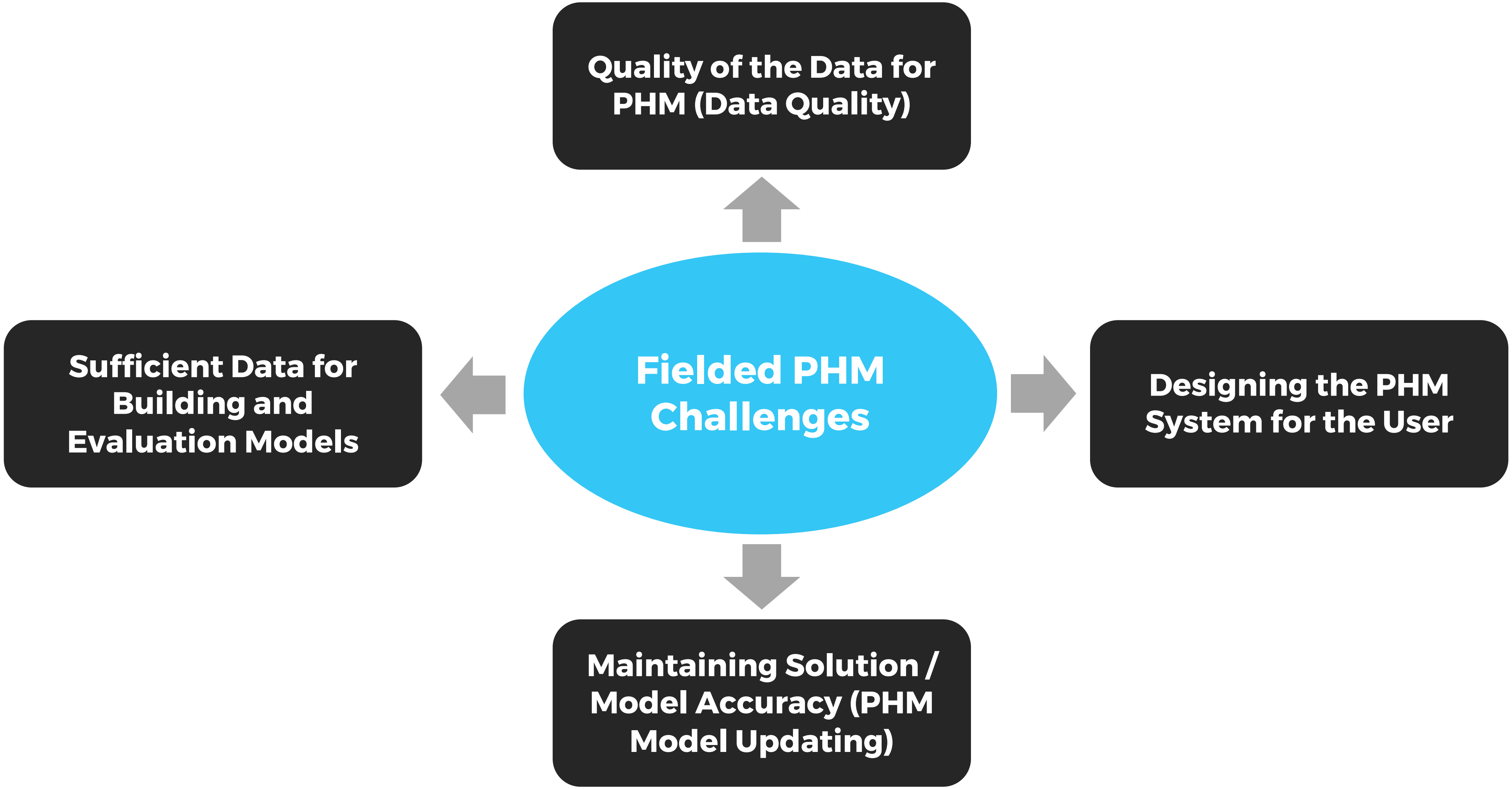
ORGANIZATION	DESCRIPTION	BENEFIT
Helicoptor Health and Usage Monitoring (HUMS)[2]	in 2008, Maj. Gen. James Myles, then commander of the Aviation and Missile Command, attributed more then $112 million in savings to HUMS	$112m in savings
GE – Power Generation[3]	GE's predictive maintenance technologies were used to monitor over 1500 gas turbines, helping to decrease plant downtime	$70m in savings
Intel[4]	Advanced factory data collection, automation, and data analytics lead to improved equipment uptime, increased manufacturing yield, and allowed maintenance to be conducted prior to failure	$9m when deployed in just one factory

LESSONS LEARNED FOR PHM SYSTEM DEVELOPMENT AND DEPLOYMENT

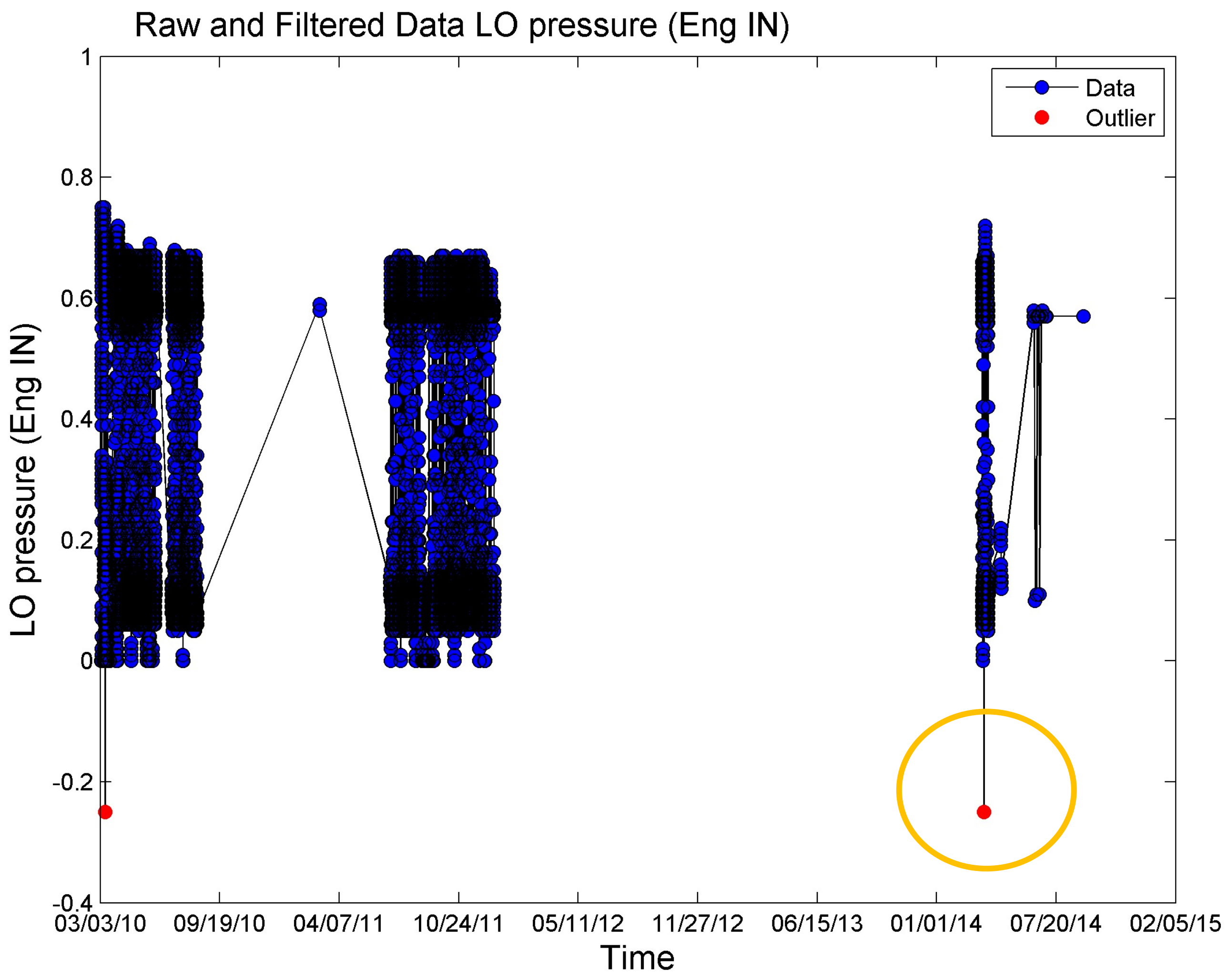
1. Start small, fail small, but do not be too hesitant to start.
2. Machine Learning and Pattern Recognition are Great, but they are not Magic.
3. Select a high value problem but not the most difficult /challenging application.
4. Use domain knowledge to ensure that you have the right data for the problem at hand.
5. The customer cares about solutions and value, do not focus on selling the platform or the technology.

Challenges in Fielded PHM Systems

CHALLENGES IN FIELDED PHM SYSTEMS



DATA QUALITY (OUTLIER REMOVAL)



Outlier removal approaches

1. **From domain knowledge, set lower and upper limits (set quite wide) to remove obvious incorrect sensor readings and outliers (example in the plot is for a pressure signal that has negative values, which must be incorrect).**

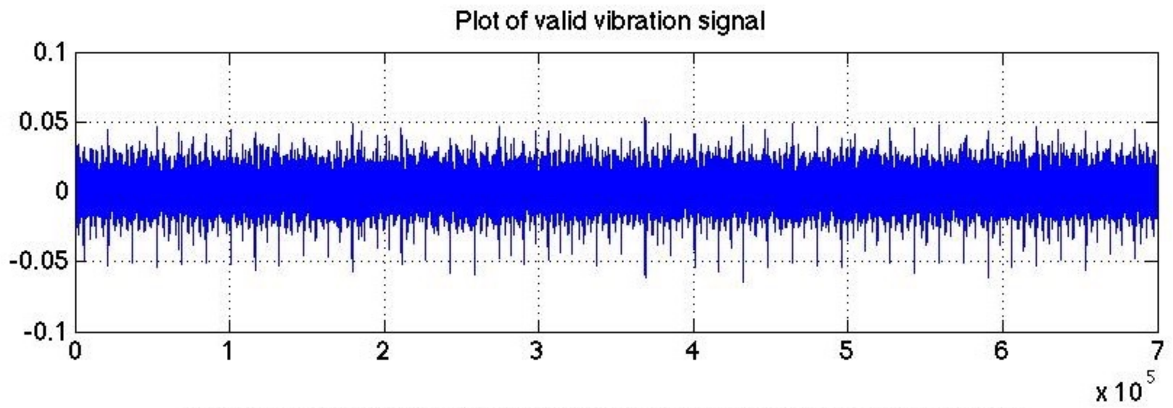
2. **Contextual outliers, such as the temperature should slowly increase with machine usage (so a value that does not follow that pattern would be an outlier).**

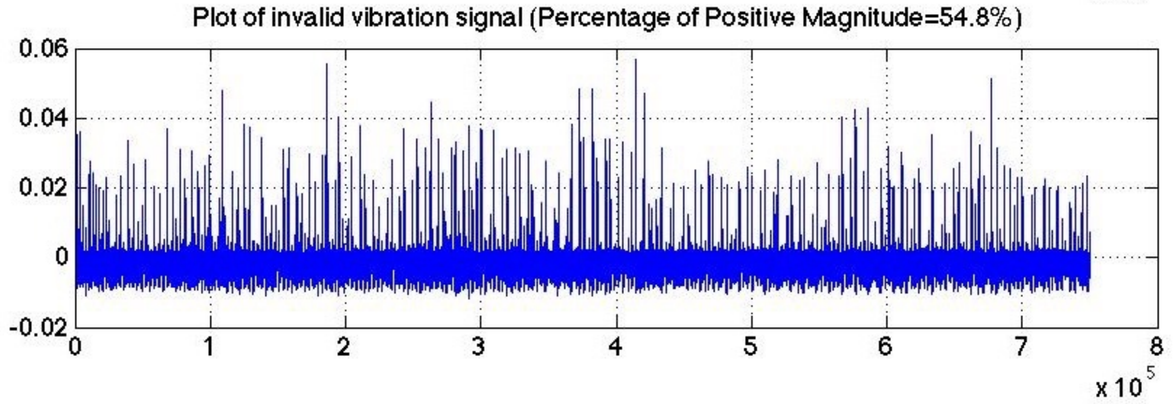
3. **Data samples with too many variables with missing values (remove that sample/row).**

4. **Pre-processing (segmentation/selection of data samples for a particular operating mode/regime).**

DATA QUALITY (HIGH FREQUENCY DATA – DATA QUALITY CHECKS)[5]

Methods	Signal Processing	Comments
RMS Check	RMS value of signal	Check overall level of signal
Energy Conservation Rule	RMS value of time and frequency domain signal	Should be equal or close to equal.
Statistical distribution rule	Normal distribution fit of signal	Ideally, should not be very far off from normal distribution
N-point check	N neighbor points with the same value	Quantization error
Positive and negative point	Portion of positive and negative points	DC-offset / Mean Value (ideal case is 50%)
U-point rule	Number of unique values	Quantization error
Z-point rule	Largest time-gap between zero-crossing	Offset /measurement error





For highly sampled data (vibration, acoustic/microphone), there are established checks to ensure that the data is correct and suitable for further analysis.

[5]Jablonski, A., & Barszcz, T. (2013). Validation of vibration measurements for heavy duty machinery diagnostics. Mechanical Systems and Signal Processing, 38(1), 248-263.

TYPICAL DATA AVAILABLE FOR TRAINING MODELS AND APPROACH

Type of Industry	Type of Assets	Existing data being collected	Data from a baseline condition	Data from a Failure Condition	PHM Approach
Discrete Manufacturing	CNC Machine Tools, Industrial Robots, Stamping, Welding	Not typically	Only after data collection system has been implemented	No	Only option is baseline-based anomaly index/health index
Power Generation / Process Industry	Pumps, turbines, compressors, fans, control valves	Yes (SCADA system)	Yes	Yes, but only many failures in a few cases	Supervised models are still difficult to consider, so anomaly index is still typically used
Automotive / Vehicle Health Monitoring	Commercial vehicles, construction/mining vehicles	Can-bus (yes), and maybe high frequency data	Yes	Yes, but only many failures in a few cases	Supervised models are still difficult to consider, so anomaly index is still typically used
Commercial Aerospace / Aviation	Fixed wing aircraft, rotorcraft	Yes (full flight, snapshot, condition indicators)	Yes	Yes, but only many failures in a few cases	Supervised models are still difficult to consider, so anomaly index is still typically used

In most cases, the use of supervised machine learning models are quite challenging, since having sensor data from the same failure mode of several instances is unlikely unless you have an existing monitoring system for several years and many assets.

MAINTAINING THE PHM SOLUTION / UPDATING MODELS

Reasons PHM Solution Models can become Inaccurate Over Time

1. After maintenance/repair, the asset is restored to a new/different baseline then originally.

2. The asset operates in new modes of operation or experience new failures modes that the model were not originally trained for.

3. The asset(s) are updated/slightly newer version compared to when PHM system was initially implemented (engineering modifications to subsystem, control system, data collection system).

- PHM solutions need to be improved and maintained over the life-cycle of the solution.

- Ideally, incorporates ways for the solution and models to be updated and improved over time is becoming an increasing important aspect for achieving PHM solutions that deliver value for the entire life-cycle.

CONSIDERATIONS FOR AN EFFECTIVE PHM SYSTEM

TYPICAL USER OF PHM SYSTEM

The user is not typically a data scientist but instead a maintenance technician

INFORMATION MUST BE USED IN DECISION MAKING PROCESS

My perspective is that the PHM system is providing health information and recommendations, and the user ultimately must decide what action (if any) is needed.

HAS TO INTEGRATE INTO THEIR DAILY ROUTINE

Training on how to use the system is important, and it is important to integrate this type of solution into their daily routine, so it is used to its full advantage

EXAMPLE WORKFLOW FOR MANUFACTURING CUSTOMER (CNC MACHINE / HYDRAULIC CLAMP SYSTEM)

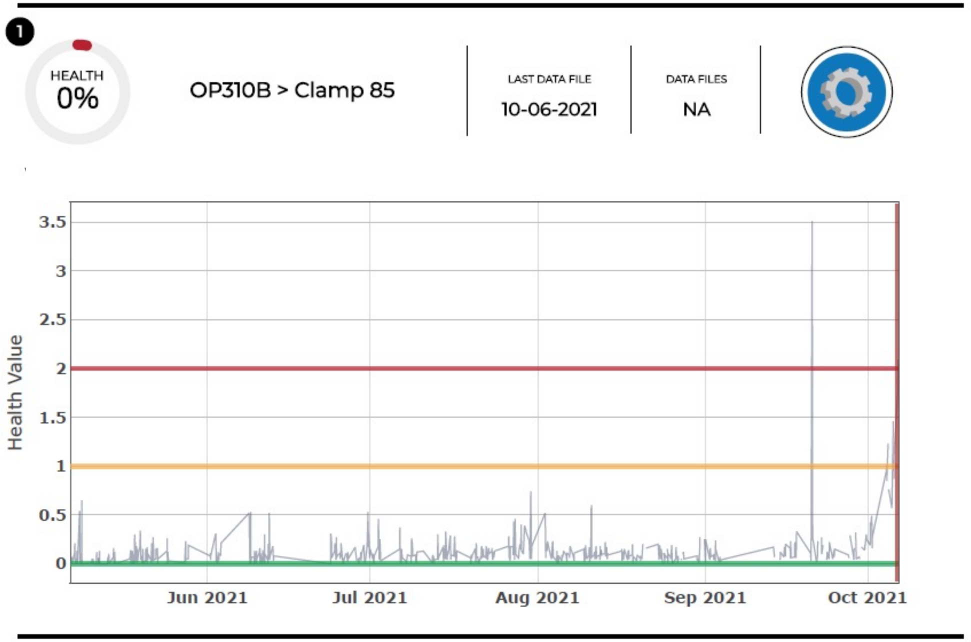
Alerts and reports are sent to users (by text/email) on developing problem

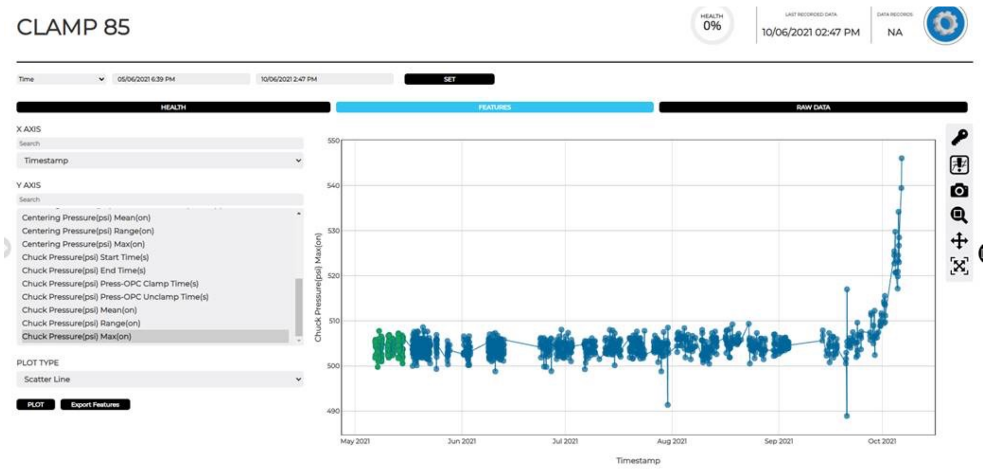
User can click on health index view for asset to see emerging trend

Contribution bar graph shows key contributing feature/variable to unhealthy condition

Visualize individual feature plot of top contributing variables

After confirming algorithm result, decide on maintenance action



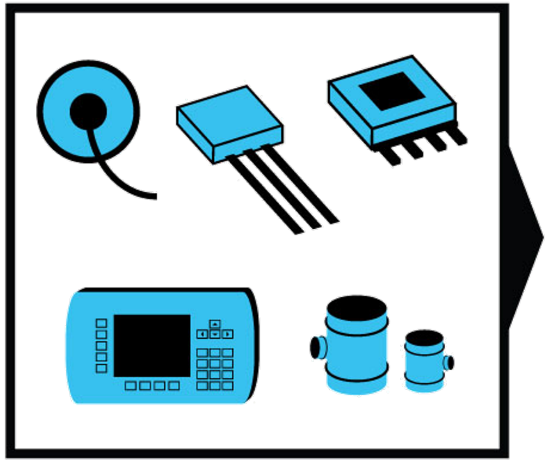


From our experience working with discrete manufacturing customers for PHM implementations, they don't have time to view the dashboard all the time; alerts and reports are critical for informing them of impending problems/failures.

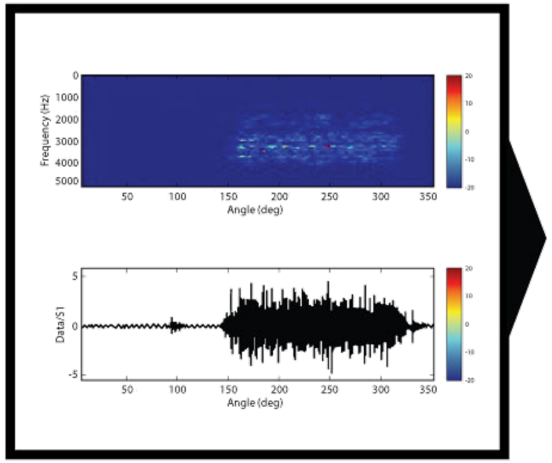
PHM Development and Deployment

DATA-DRIVEN PROGNOSTICS AND HEALTH MANAGEMENT DEVELOPMENT

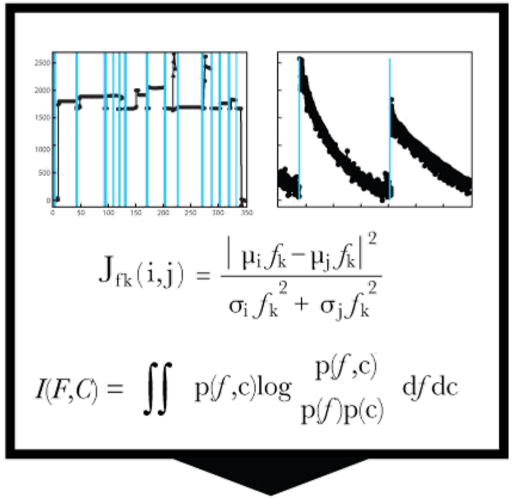
Data Collection

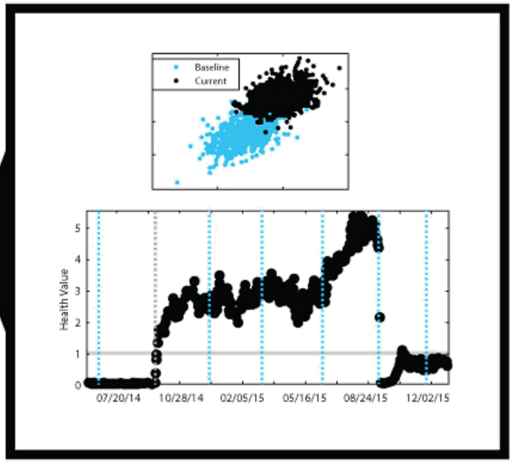


Signal Processing

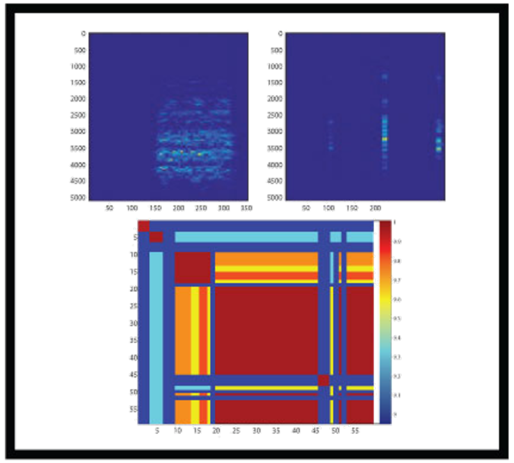


Feature Extraction

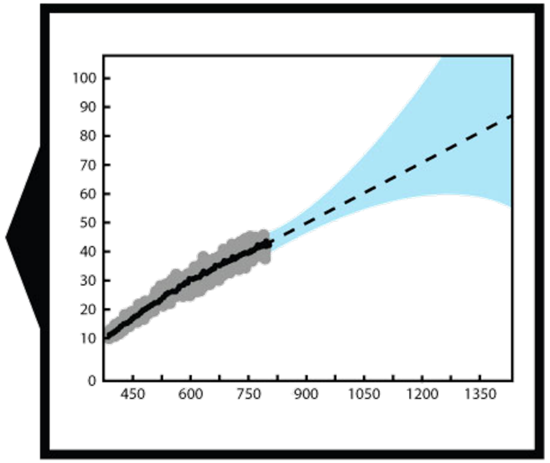




Fault Diagnosis



Trending / Prediction



Health Assessment

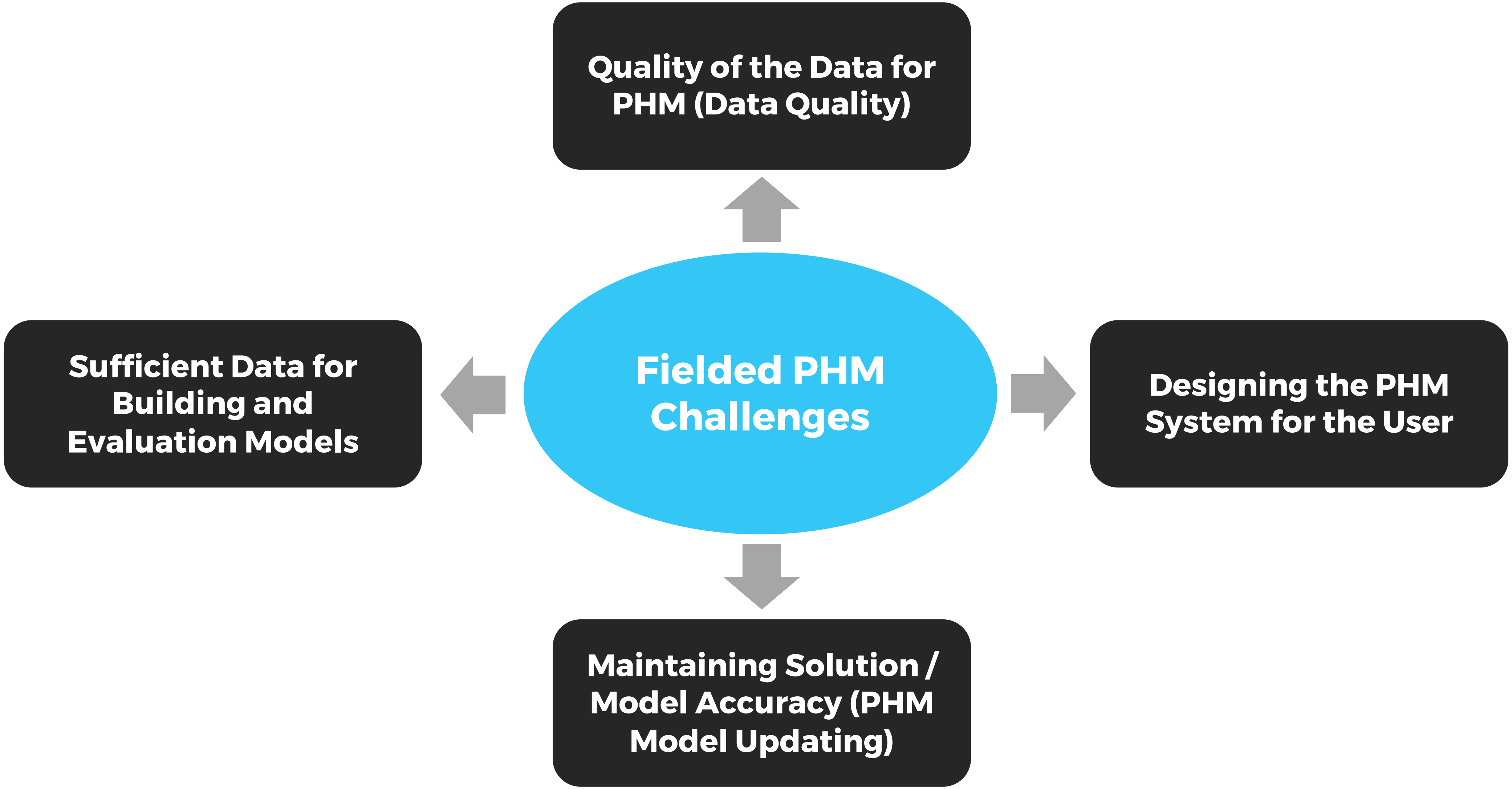
DATA COLLECTION

Data Collection

- **Leverage existing data sources (SCADA, PLC data) but do consider adding external sensors**
- **Use domain knowledge / experience for determining what data to collect / what sensors to use**
- **Trigger data collection (such as capturing data on a cycle-by-cycle basis)**
- **Align data sources from different sampling rates**

It is less about collecting a large amount of data and more about collecting higher quality data and including more intelligence into the data collection.

CHALLENGES IN FIELDED PHM SYSTEMS



BEST PRACTICES FOR WORKING TOWARDS PROGNOSTICS (ACHIEVING THE P IN PHM)

Best Practices

- Criticality Analysis – Select Right Machine and/or Process
- Have Vision and Approval from Top Management
- Refine approach and improve models over time
- Determine if Failure Prediction is Needed
- Select and evaluate appropriate prognostic approaches
- Obtain domain insight on whether failure mode has degradation trend, intermittent, abrupt
- Evaluate whether enough historical data or domain knowledge is provided for prognostics
- Evaluate feasibility for early detection (enough lead time)

CHALLENGES IN PROGNOSTICS

1. **Prognostics depends on Robust Early Detection and Potential Correct Diagnosis** – Typically a prognostic method would be trigged after a problem is detected at an early stage. It might be also helpful to diagnosis the problem since different failure modes have different trajectories.

2. **Data-Driven Prognostic Methods Would Need Past Examples of Failure** – The model training requirement for prognostics is higher than early detection and requires at least 5 to 10 past examples from healthy (or early detection) to failure.

3. **Not all Problems and Failure Modes are Suitable for Prognostics** – Some problems are more intermittent, caused by manufacturing issues and already present, or might not have a sensor that can accurately track its severity well over time.

4. **Failure Itself is Hard to Define** – What is considered a failure varies by application and even the decision maker—the definition could be based on a physical defect size, functional performance, or a visual inspection of the machine or equipment.

Industrial Case Studies

INDUSTRIAL USE CASE SUMMARY

NO.	Use Case	Key Takeaway
1	Automotive Manufacturing and Industrial Robots	A graceful degradation trend – a case for prognostics
2	Wheel Manufacturing Use Case	The complete implementation process and early detection
3	Oil /Gas Application – Reciprocating Pump Health Monitoring	Diagnosis methods and analysis algorithms
4	Steel Manufacturing – Early detection of failure	Waveform vs. feature-based methods
5	Aerospace Application	The importance of exploration in feature engineering

AUTOMOTIVE MANUFACTURING

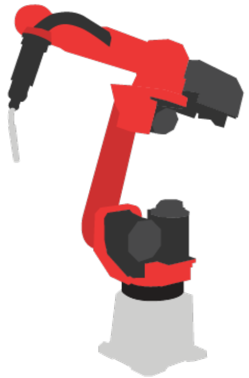
Predictive Monitoring of Industrial Robots

CASE STUDY

BUSINESS CASE FOR HEALTH MONITORING OF INDUSTRIAL ROBOTS

500
Robots in a Factory

$10,000
Average Cost of 1-Minute of Downtime



30
Number of Robot Failures During Production in 1 Year

30 minutes
Average Unplanned Downtime for Each Robot Failure

$300,000
Cost of a Single Robot Failure

50%
Assumed Numbers of Failures FS Predicts

$4,500,000
Estimated Annual Savings per Factory

PAST CASES IN ROBOT HEALTH MONITORING

Customer	Fault Type	Description
Customer A	Faulty motor brake in Axis 5 resulted in a position accuracy issue.	A blind trial in which the customer replaced Axis 5 motor with a bad motor to test our algorithm.
	Degraded motor brake in Axis 5 resulted in position accuracy issue (long term trend).	This robot exhibited a long-term trend, and the motor brake was degraded (eventually would have caused collisions).
Customer B	Grease in Joint 3 was purged (gearbox issue).	This problem had a clear trend.
	Motor brake failure in Axis 3	Detection was possible 1-2 weeks ahead of time.

- For Customer A, they had **25-30** failures during production prior to our engagement and at least **50% of the motor replacements were due to position accuracy issues from motor brake degradation and failure.**
- In general, **position accuracy failures** (motor brake) and **gearbox related issues** were the most common failure modes.

ROBOT MAINTENANCE STRATEGIES AND COMMON FAILURE MODES

FREQUENCY OF OCCURRENCE

Preventive Maintenance

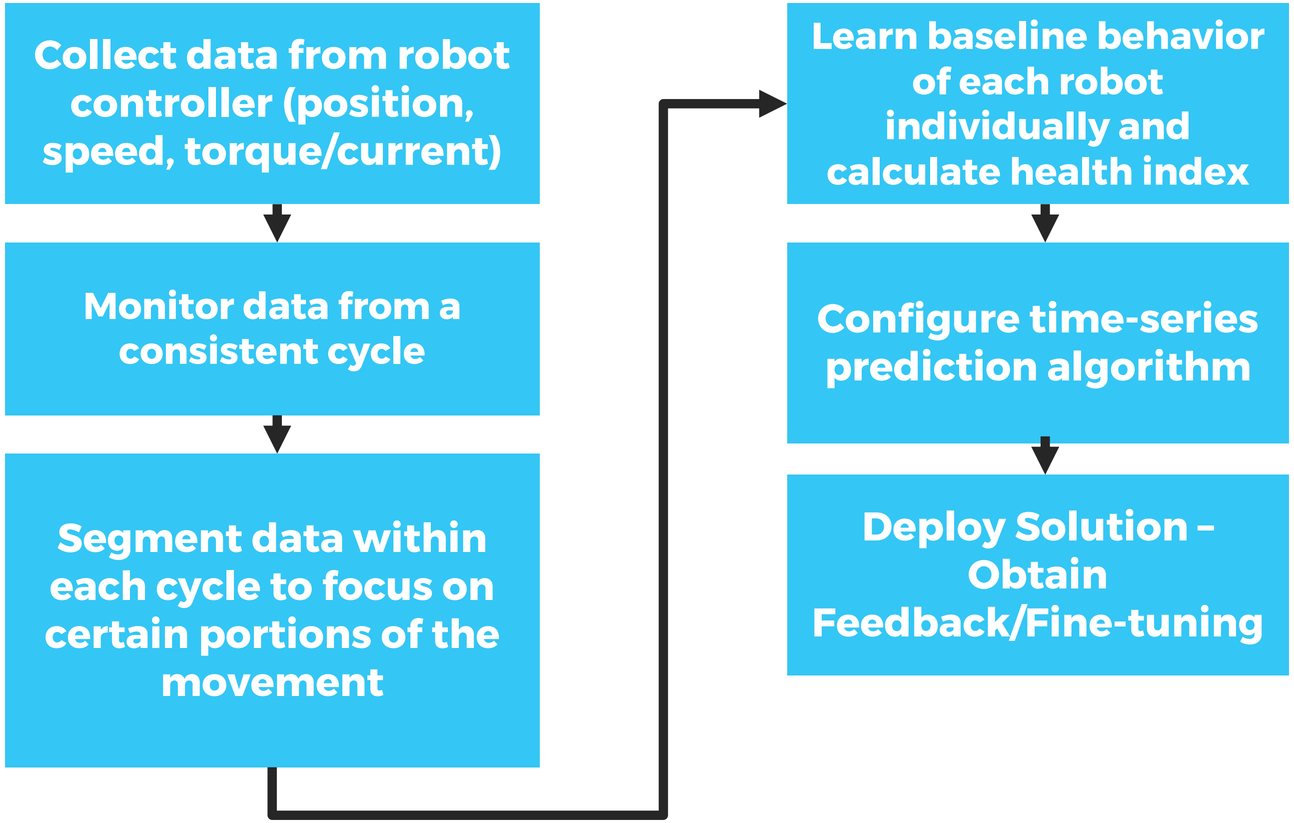
- Cable Failure
- End-effector Components
- Dead Battery
- Mild Lubrication Loss

Predictive Maintenance

- Worn Belt
- Motor Brake Failure
- Gear Backlash
- Lubrication Starvation
- Bearing Failure

DOWNTIME COST / IMPACT

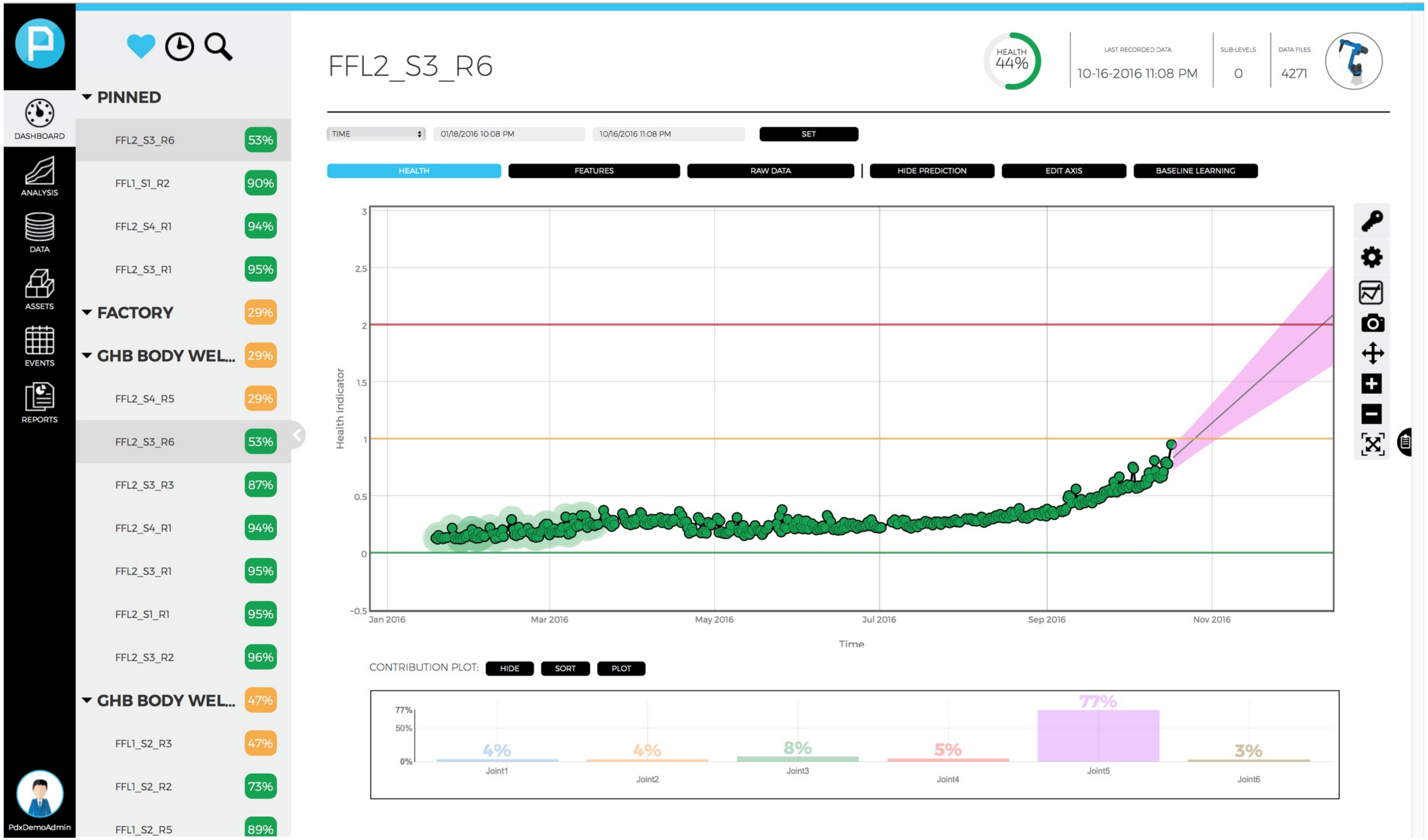
EXAMPLE FLOW CHART FOR PREDICTIVE MONITORING OF INDUSTRIAL ROBOTS



- For industrial robot predictive monitoring, one should initially consider the feasibility of collecting data from the robot controller (if it is not feasible, add on sensors such as motor current can be considered).

- Typically, it is unlikely to have data from many past failures, so it lends itself to a baseline-based health index approach as opposed to supervised machine learning models.

INDUSTRIAL ROBOT PREDICTIVE MONITORING



AUTOMOTIVE MANUFACTURING

Predictive Monitoring of Key Equipment for a Wheel Manufacturing Plant

CASE STUDY

WHEEL SPINNER PREDICTIVE MONITORING

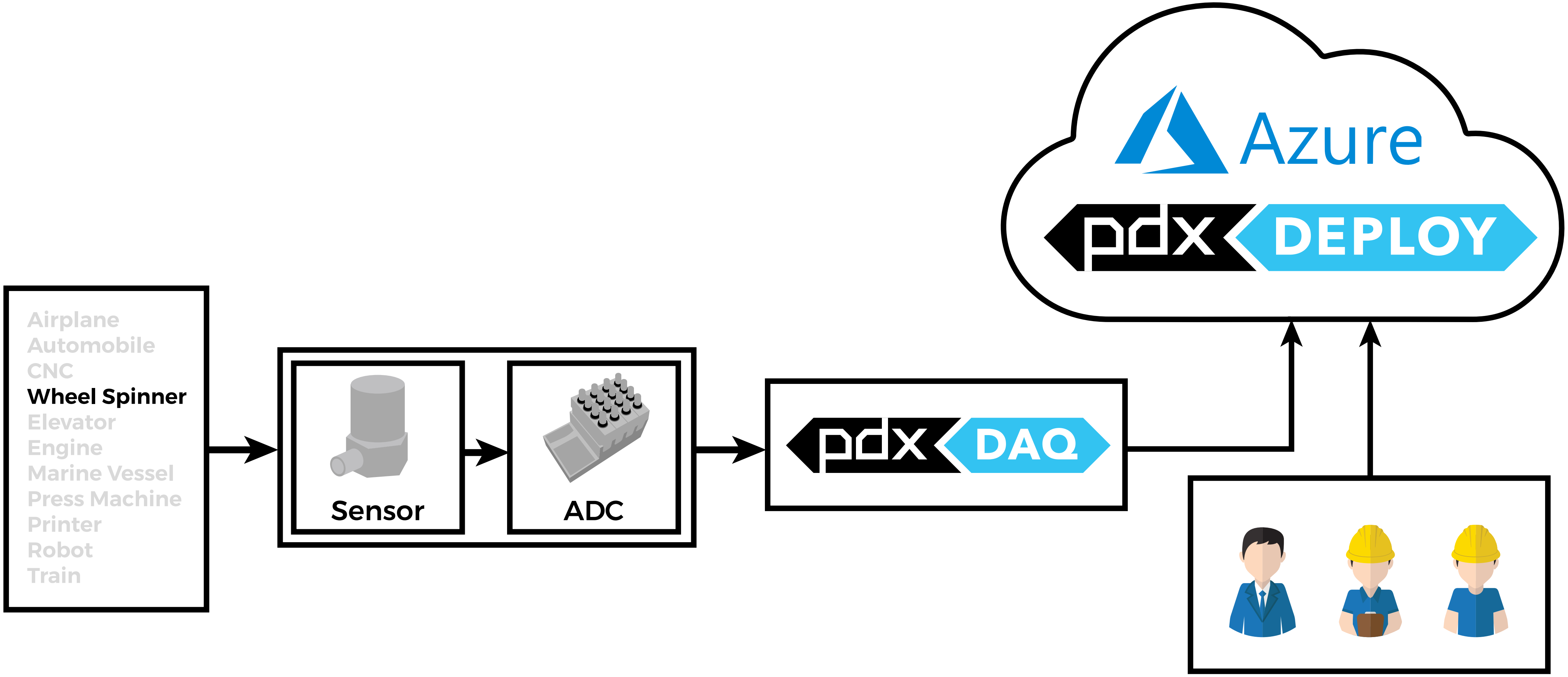
APPLICATION & BACKGROUND

- The client featured in this case study is a global **automotive supplier** of wheels.
- The engagement focused on delivering a predictive monitoring solution for **roll-forming machines and wheel spinners**.
- During a pre-project workshop, the key components and measured signals were determined by our automation and instrumentation team.

IMPACT

- The project aims to provide more visibility for wheel spinner equipment and provide analytics related to **predictive maintenance, process monitoring, and product quality**.

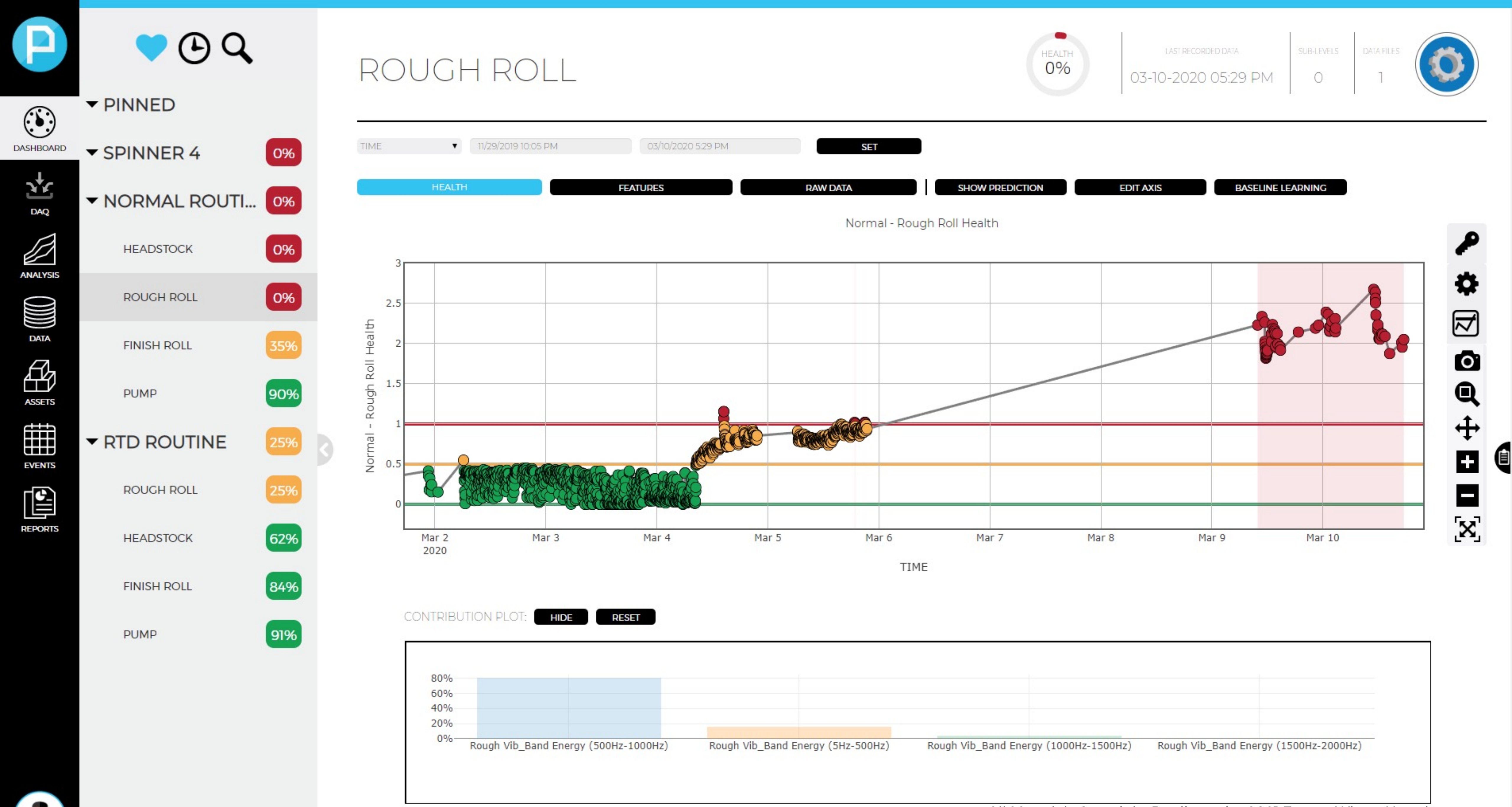
IMPLEMENTATION FRAMEWORK



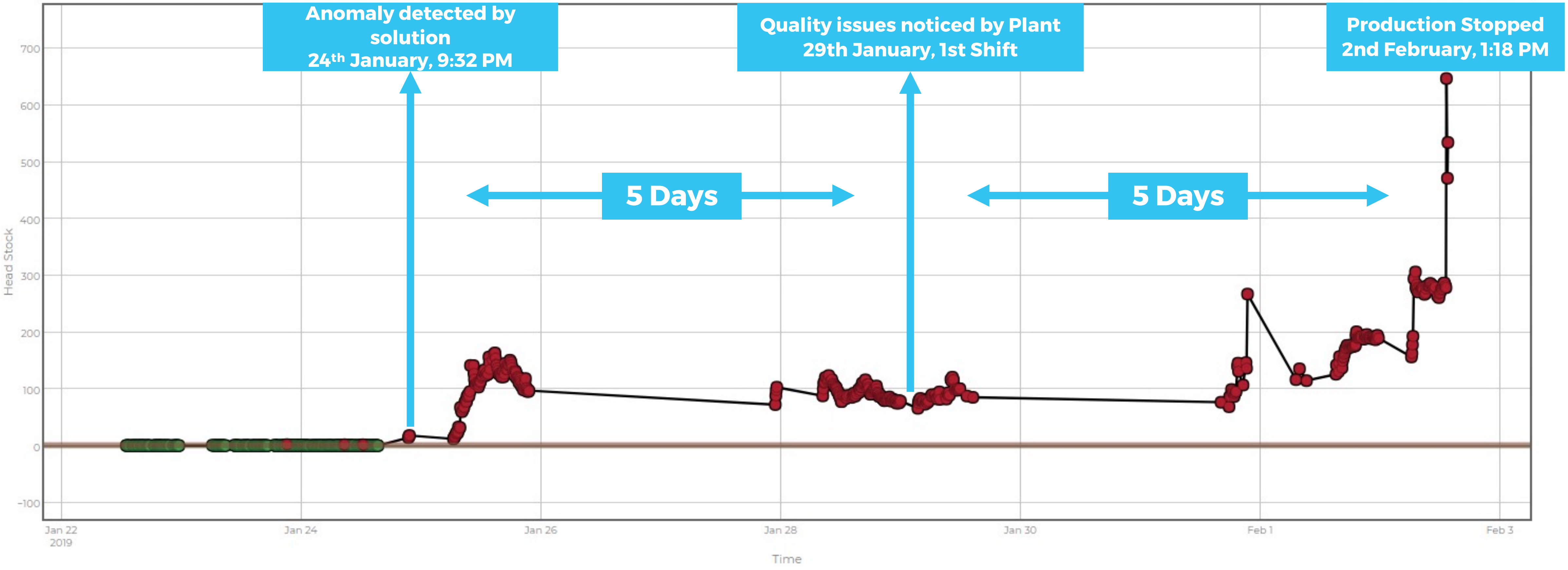
WHEEL SPINNER DATA SUMMARY

This table lists the sensors, signals, and sampling rate required to develop a predictive model for this application.

Sensor	Signal	Sampling Rate	Number
Accelerometers	Vibration	High	4
Flow Meters	Flow Rate	Low	2
Pressure Transducers	Accumulator Pressure	Low	2


DASHBOARD
DAQ
ANALYSIS
DATA
ASSETS
EVENTS
REPORTS
PINNED
SPINNER 4 0%
NORMAL ROUTI... 0%
HEADSTOCK 0%
ROUGH ROLL 0%
FINISH ROLL 35%
PUMP 90%
RTD ROUTINE 25%
ROUGH ROLL 25%
HEADSTOCK 62%
FINISH ROLL 84%
PUMP 91%
ROUGH ROLL
HEALTH 0%
03-10-2020 05:29 PM
0
1
TIME
11/29/2019 10:05 PM
03/10/2020 5:29 PM
SET
HEALTH
FEATURES
RAW DATA
SHOW PREDICTION
EDIT AXIS
BASELINE LEARNING
Normal - Rough Roll Health
Normal - Rough Roll Health
0
0.5
1
1.5
2
2.5
3
Mar 2 2020
Mar 3
Mar 4
Mar 5
Mar 6
Mar 7
Mar 8
Mar 9
Mar 10
TIME
CONTRIBUTION PLOT:
HIDE
RESET
80%
60%
40%
20%
0%
Rough Vib_Band Energy (500Hz-1000Hz)
Rough Vib_Band Energy (5Hz-500Hz)
Rough Vib_Band Energy (1000Hz-1500Hz)
Rough Vib_Band Energy (1500Hz-2000Hz)

HEALTH INDEX (SPINNER EQUIPMENT) – SPINNER VALIDATION – HEAD STOCK ISSUE – TIMELINE



CONCLUSIONS

- The pilot **successfully demonstrated all key aspects of a predictive monitoring system** (IOT/data collection, analytics, and deployment).
- The deployed system has already detected the early symptoms of potential failures for the spinner equipment (2 events).
- For these events, the issue is detected **well before the failure**, such as **10 days** for the head-stock failure and customer has reported **annual savings of over 200,000 USD** from pilot solution.
- The solution is currently deployed for a spinner and a roll-forming machine. It is expected to be expanded to the remaining roll-forming and spinner machines at the facility, as well as other facilities.

PROCESS INDUSTRY / OIL & GAS

Predictive Monitoring of Reciprocating Pumps

CASE STUDY

HEALTH MONITORING OF RECIPROCATING PUMPS

BACKGROUND

- Oil & gas client
- Monitor health condition of reciprocating pumps
- Needed a health model that indicates and diagnoses potential failures

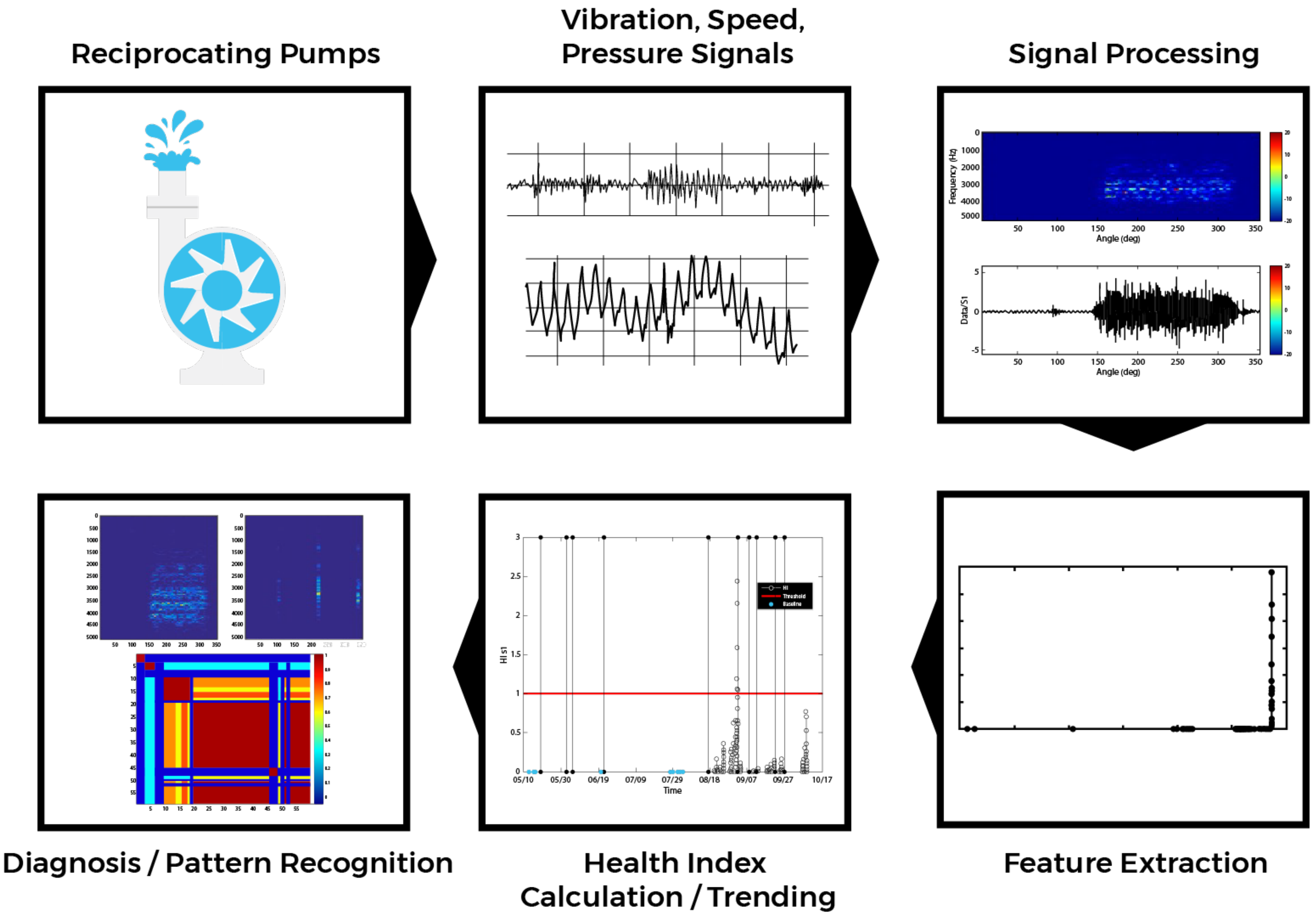
IMPACT

- A vibration-based health monitoring solution combining advanced signal processing, baseline-based health assessment and a pattern recognition diagnosis
- Successful results for test-bed data as well as two pumps in the field

PUMP OVERVIEW

Machine / Controller Information	Signals	Failure Modes
Centrifugal pump, Reciprocating Pumps	Vibration Pressure RPM Flow rate measure	Bearing faults (fatigue spall, lubrication), Seals /leakage Cavitation

HEALTH MONITORING OF RECIPROCATING PUMP

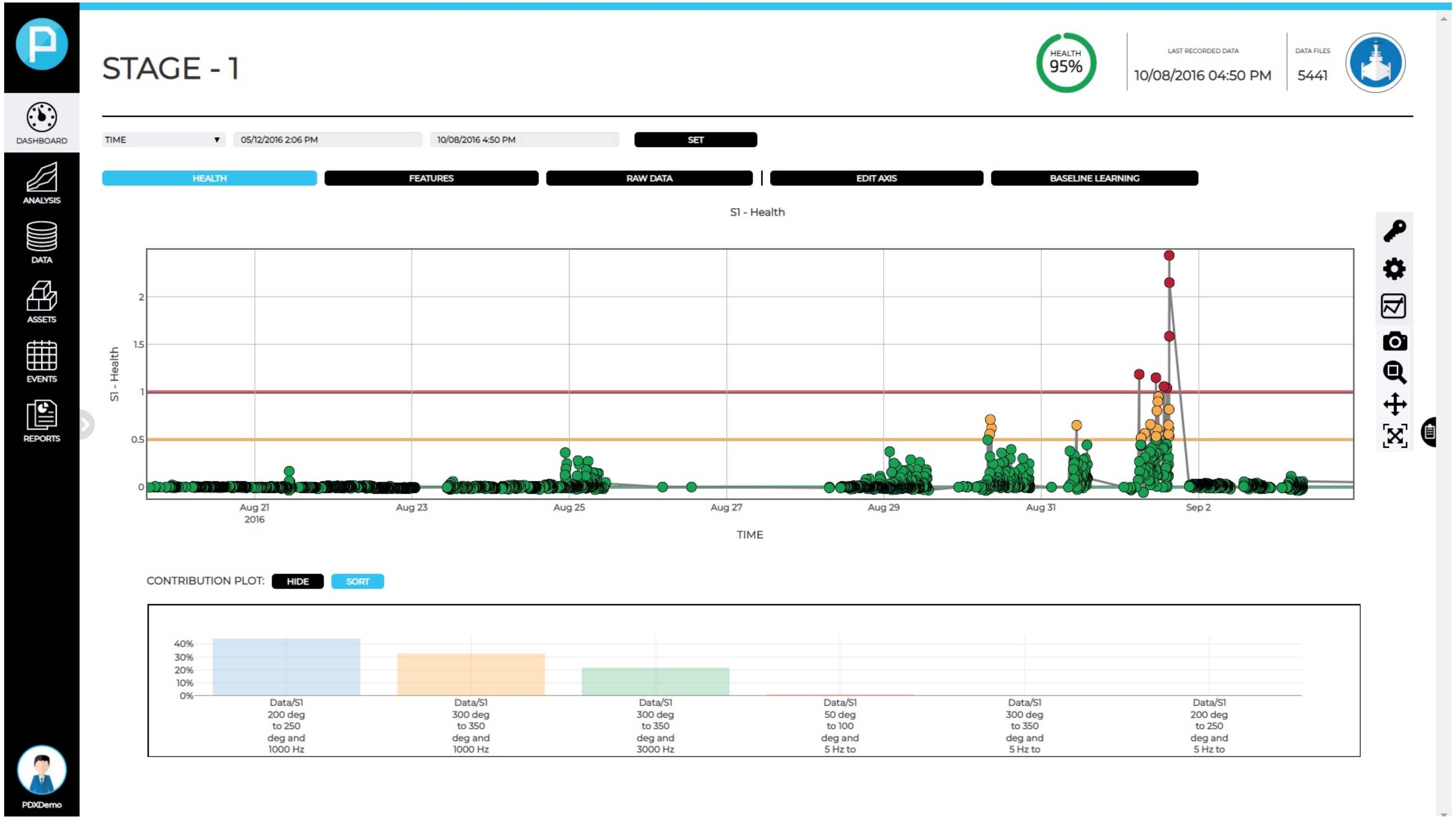


RECIPROCATING PUMPS HEALTH MONITORING – FEATURE VIEW

- Time-frequency analysis and features had a clear and significant trend leading up to the leak event.
- Other anomalies were related to sensor problems.
- The multivariate baseline anomaly detection method incorporated multiple aspects to have a robust assessment of the pump's health.

RECIPROCATING PUMPS HEALTH MONITORING – HEALTH INDEX

- The predictive monitoring solution for the reciprocating pumps was able to have an early detection of a potential leak event.
- The solution was validated with data from both a test-bed and the field.



STEEL MANUFACTURING

Steel Manufacturing – Early Detection of Roller Failure

CASE STUDY

EARLY DETECTION OF ROLLER FAILURE IN STEEL MANUFACTURING

BACKGROUND

- Stretch reducing mill for steel tubes
- A damaged roller causes deformation in the steel tubes
- The aim was to detect early signs of failure to prevent them

IMPACT

- Developed a health analysis approach that could detect changes in the waveform of the motor current for each roller
- Could successfully detect all known roller faults, with very few false alarms

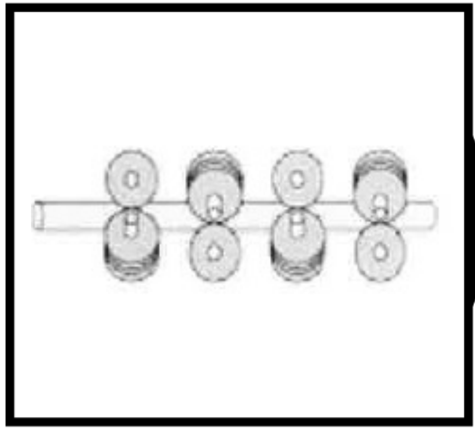
PROBLEM DESCRIPTION AND DATASET OVERVIEW

- The steels tube pass through a set of 24 stands to attain the desired diameter.
- A damaged roller in any of these 24 stands causes a deformation in steel tubes.
- Motor current for each stand was collected, along with maintenance data

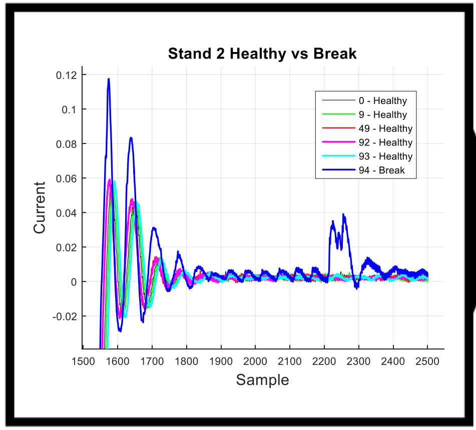
Case #	Faulty Stand	Defect
1	2	Break
2	1	Break
3	14	Scratches Cracks
4	6	Scratches Break
5	4	Break
6	8	Break
7	5	Break

ANALYSIS APPROACH - EARLY SYMPTOM DETECTION OF REDUCER ROLLER DAMAGE

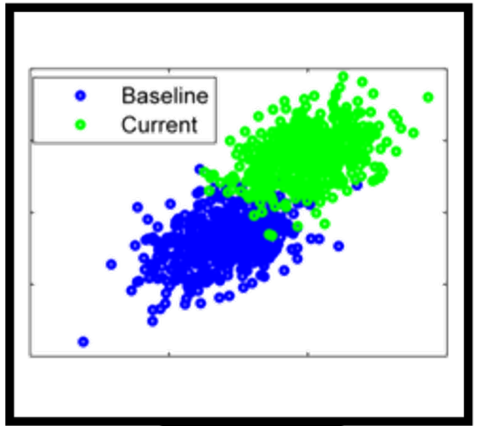
Stretch Reducing Mill

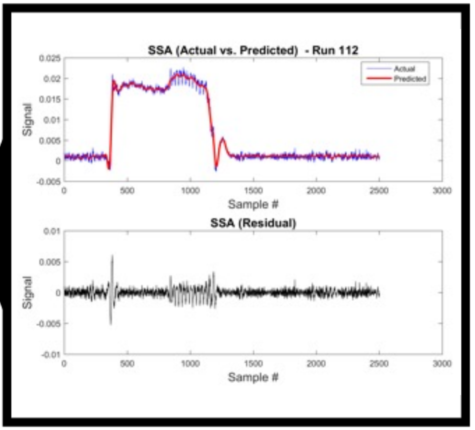


Motor Current Waveform

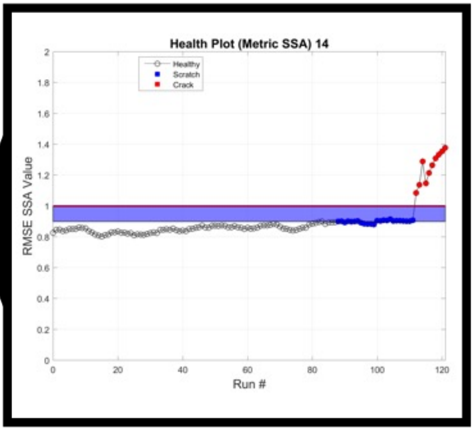


Baseline Modeling

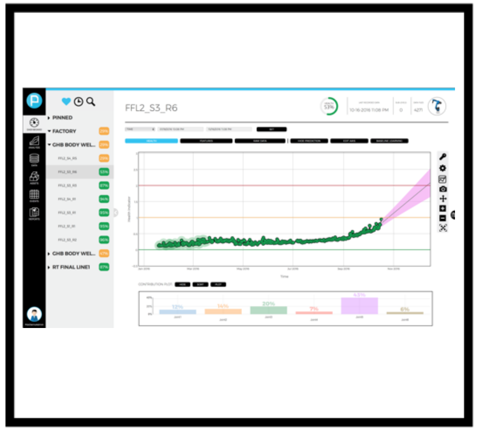




Residual Calculation

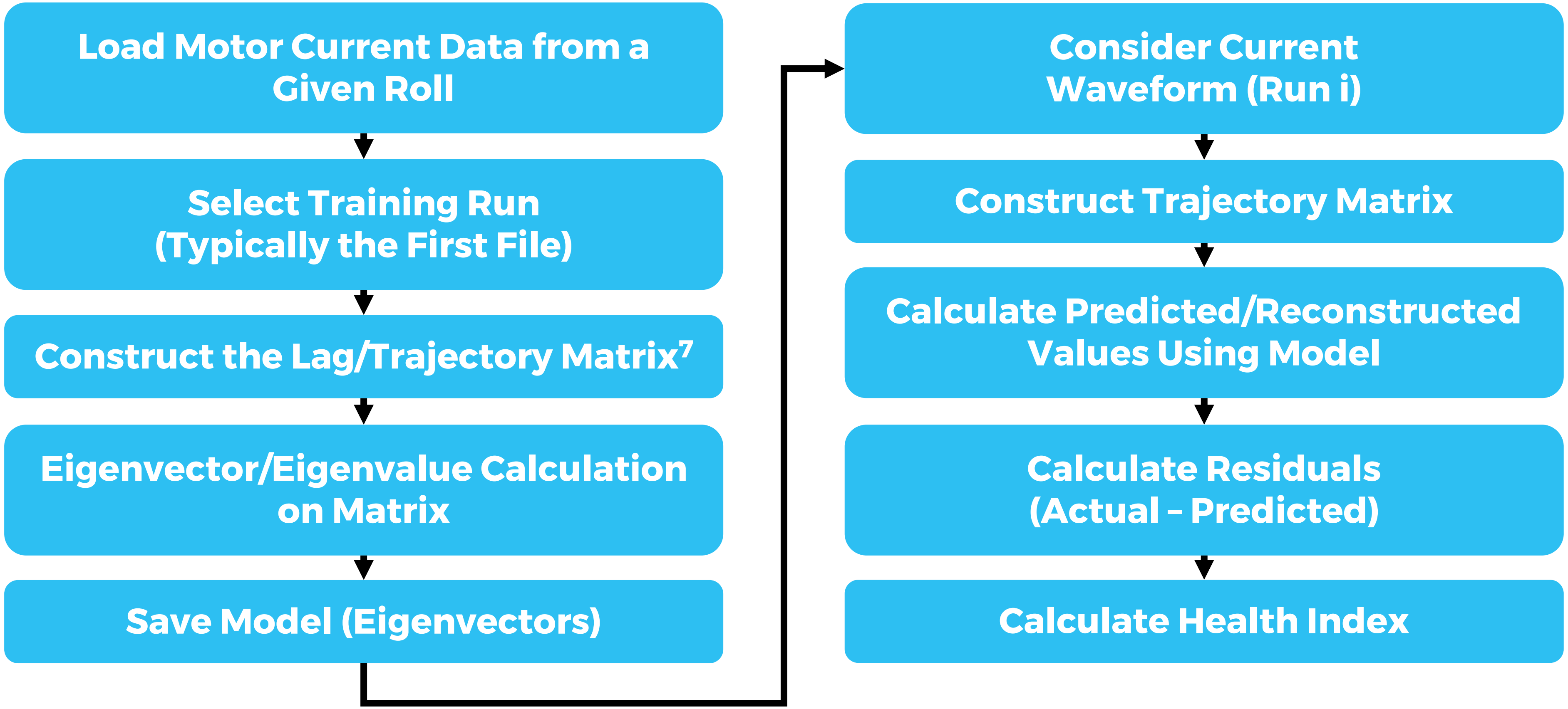


Early Alert Health Index



Visualization

SINGLE SPECTRUM ANALYSIS METHOD



The SSA time-series anomaly detection method is an effective approach for this application.

[7]Golyandina, N., & Zhigljavsky, A. (2013). Basic SSA. In *Singular Spectrum Analysis for Time Series* (pp. 11-70). Springer Berlin Heidelberg.

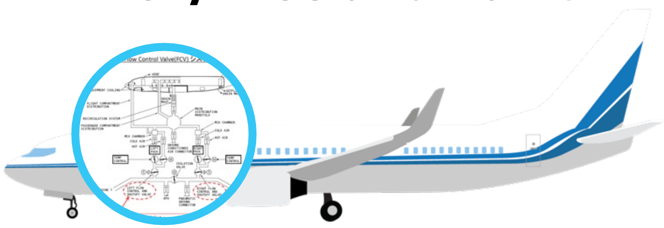
AEROSPACE

Predictive Monitoring of Key Aircraft Components

CASE STUDY

PROBLEM DEFINITION / PROBLEM TYPE (VALVE)

B737/B738 and Valve



Valve Failure Key Questions?

- Can We Find an Early Indication?
- Can we diagnosis the failure?
- Can we Predict FCV Life

Potential Early Symptoms?

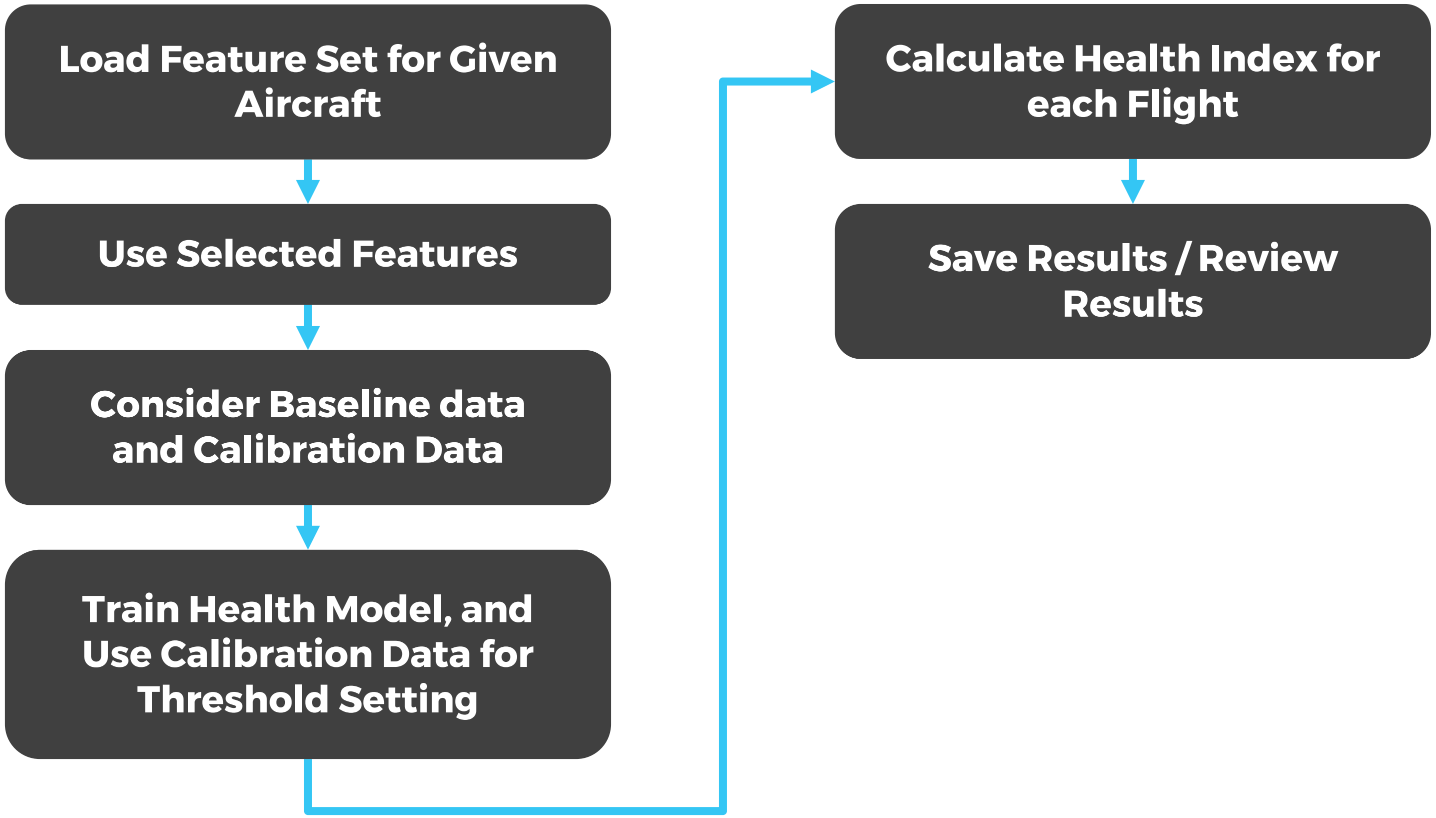
- Sluggish control of valve / output valve position
- Engine N1 response time taking longer
- Manifold bleed pressure unexpected values

Analysis Approaches

- Waveform anomaly detection models
- **Feature-based anomaly detection**
- AI and ML-Based Life Prediction

After evaluating several methods, we have made more effort on the feature-based analysis model (since we found some promising features).

FEATURE BASED HEALTH INDEX APPROACH



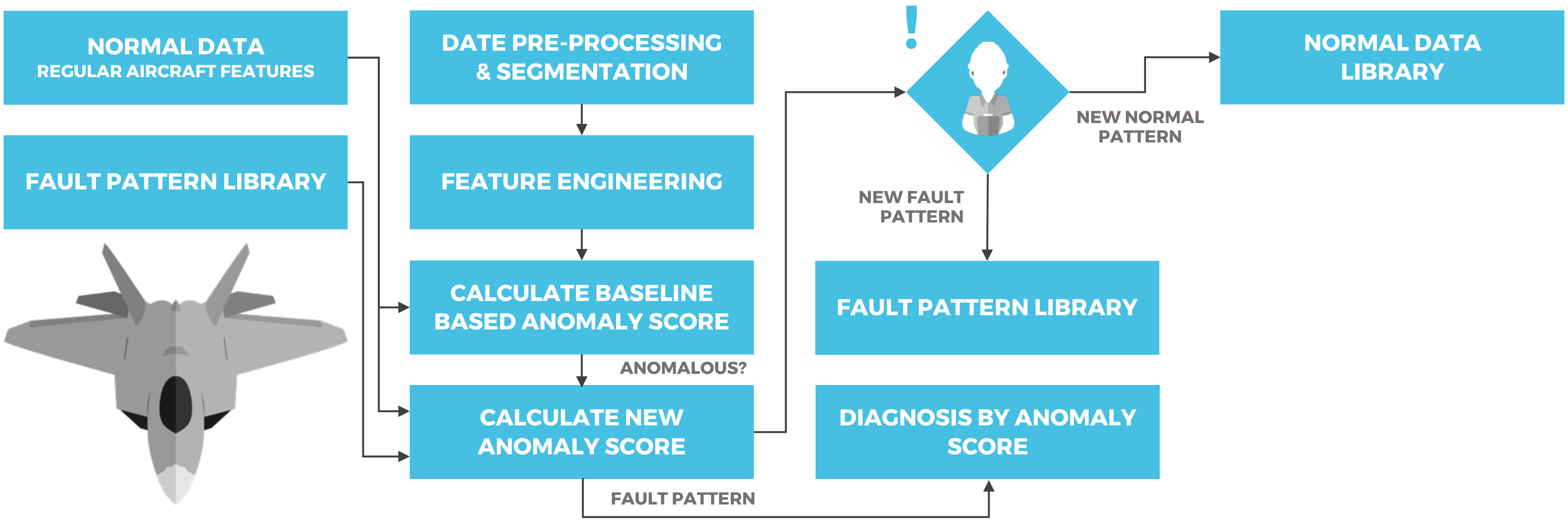
The idea behind this approach is to use these key features, and to build a multivariate health model that will provide an early indication of the emerging valve problem.

New Developments and Concluding Remarks

NEW DEVELOPMENTS FOR PHM SOLUTIONS

NEW DEVELOPMENT	DESCRIPTION	BENEFITS
Failure Diagnosis and Labelling with Human-in-the Loop	This new development allows for the models to learn over time for improved health monitoring and diagnosis	Early identification of the source of the pending failure
		Improved failure diagnosis accuracy
		Ability to use expert knowledge to add failure types
High-Mix / Low-Volume Manufacturing	This new development will address a key challenge in deploying predictive solutions for high-mix manufacturing by minimizing the affects of changing production conditions, parts being made, or processes being run on solution accuracy.	Expansion of predictive solutions to additional applications, industries and market segments
		Improved prediction accuracy
		Increased solution robustness
		Reduction of false alarms
Explainable AI	This new development includes novel approaches that better incorporate domain knowledge, reveal relationships among interconnected processes, and overall provide an additional layer of information to the user.	Improved understanding of underlying processes affecting asset health and product quality
		Drive more informed and improved decision making
		Increased solution lifecycle with model updating and retraining

FEATURED NEW DEVELOPMENT:
FAULT LABELLING & DIAGNOSIS WITH HUMAN IN THE LOOP



- **This framework can enable the diagnosis of faults at an early stage, as well as detect when a new fault pattern is occurring.**
- **With human-in-the loop, new patterns can be labeled and learned over time, resulting in more accuracy and robustness.**

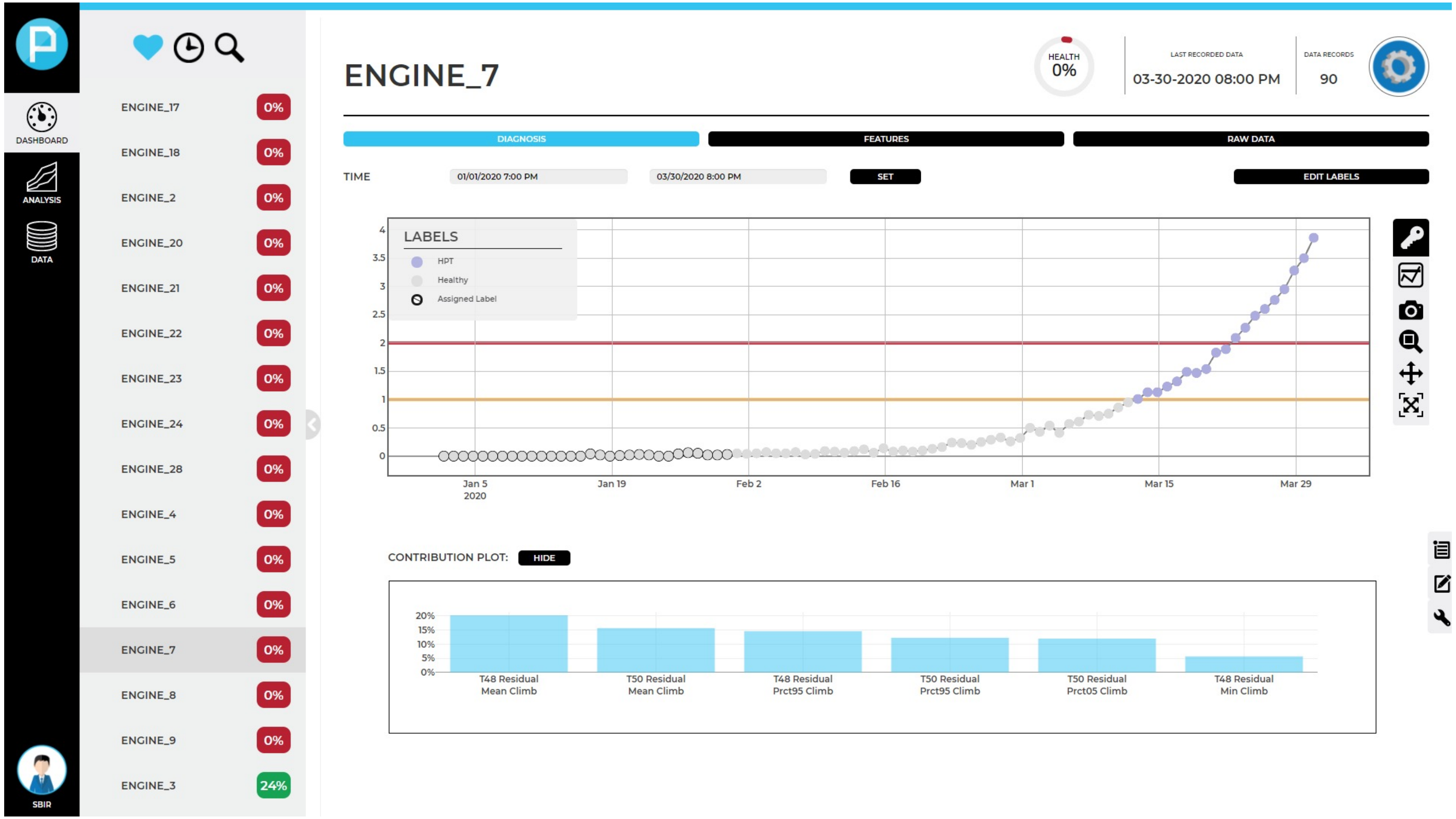
SOFTWARE PROTOTYPE

Anomalies are labeled as new pattern if do not match existing fault pattern

- Users can label points and software can use this information moving forward
- Anomalies that match that pattern moving forward would be diagnosed with that fault condition

New health modes of operation

- New modes of operation might cause system to think asset is anomalous
- After appropriate labeling, system can learn this is normal and this will be reflected in the health index



CONCLUDING REMARKS

- Prognostic and health management solutions can provide significant value to various industries if applied correctly, with the biggest business driver being the reduction in unplanned downtime.

- Many challenges exist that might be overlooked when considering just the initial development and deployment of a PHM solution in the field. It is important to consider the life-cycle and maintenance/updating of the PHM solution.

- It is very difficult to have a model that can maintain accuracy for a long period of time as new assets are added, and unforeseen conditions arise. Having a solution that can be easily updated or adjusted is needed for many of these applications.

- Many applications, especially in manufacturing, do not have data readily available that is well suited for supervised machine learning approaches. Feature engineering and unsupervised / anomaly detection methods are more suited for these applications and perhaps more University research should be focused on these topics.

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Thank You!

Predictronics
6824 Ashfield Dr
Cincinnati, OH 45242
+1 (513) 792-8090
contact@predictronics.com
www.predictronics.com

David N. Siegel, PhD
Chief Technology Officer
Predictronics
siegel@predictronics.com
+1 (513) 290-8163

Edzel R. Lapira, PhD
Chief Executive Officer
Predictronics
lapira@predictronics.com
+1 (513) 680-1662