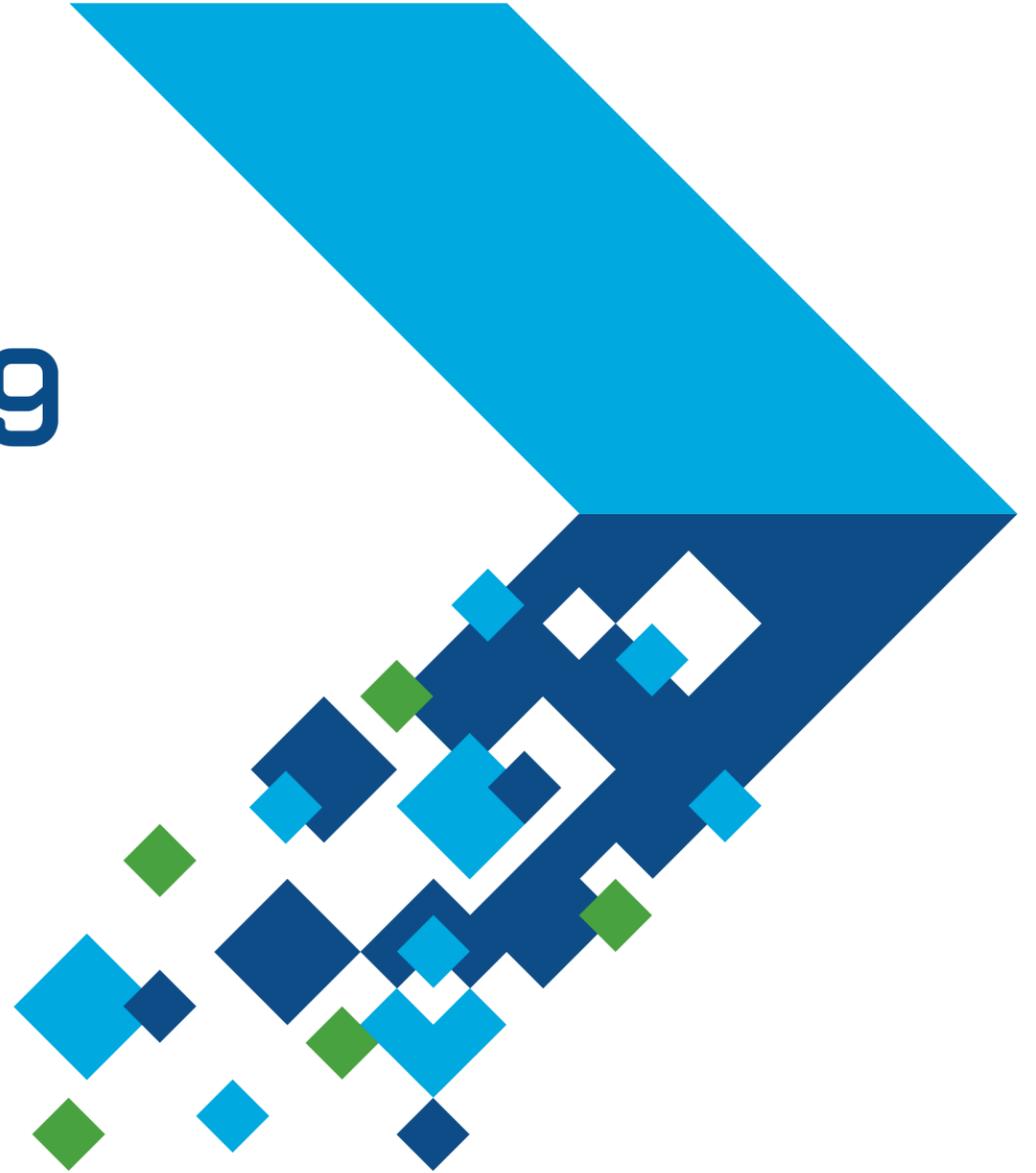




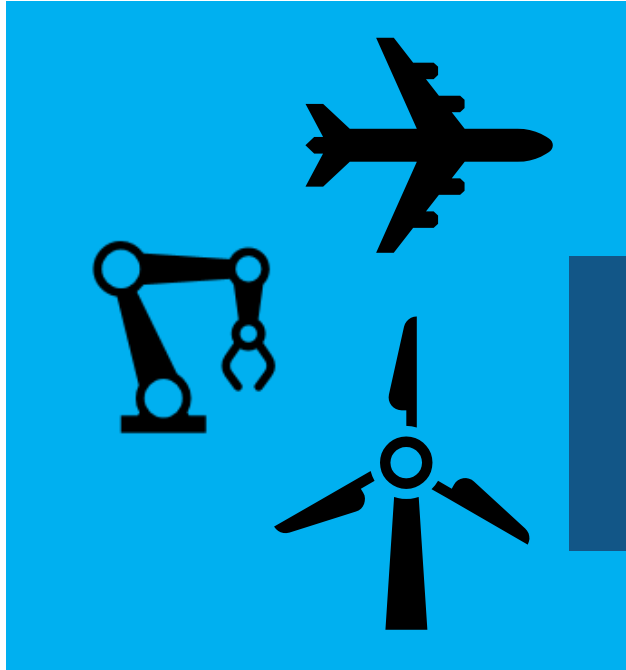
MATLAB EXPO 2019

Deploying AI for Near Real-Time Decisions

Branko Dijkstra



The Need for Large-Scale Streaming



Predictive Maintenance

Increase Operational Efficiency
Reduce Unplanned Downtime

Jet engine: ~800TB per day
Turbine: ~ 2 TB per day
Crusher: ~10 Mb per day
Washing Machine: ~10kb/day

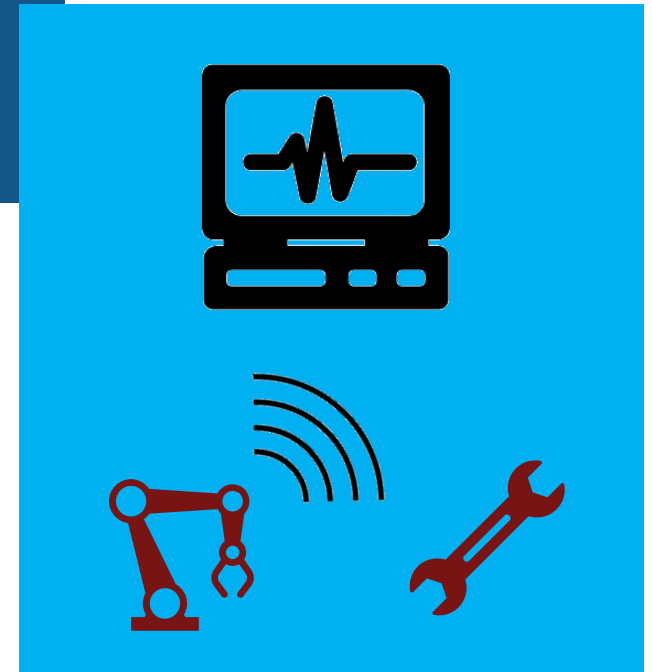
**More applications require
near real-time analytics**

Medical Devices

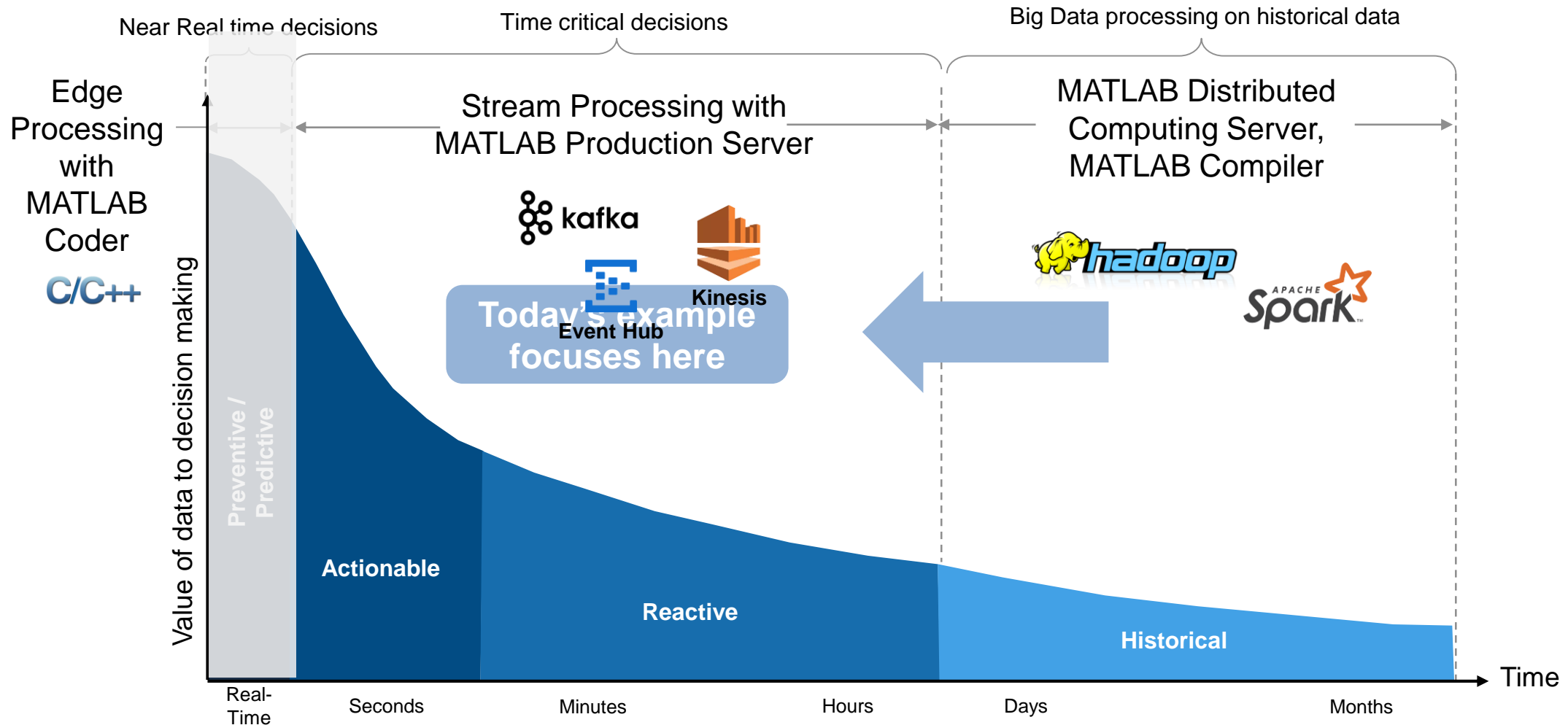
Patient Safety
Better Treatment Outcomes

Manufacture/Processing

Process Input Variation
Maintenance Planning



Why stream processing?

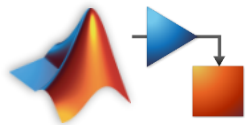


Our Project: Develop and operationalize a machine learning model to predict failures in industrial pumps



Process Engineer

Develops models
in MATLAB and
Simulink



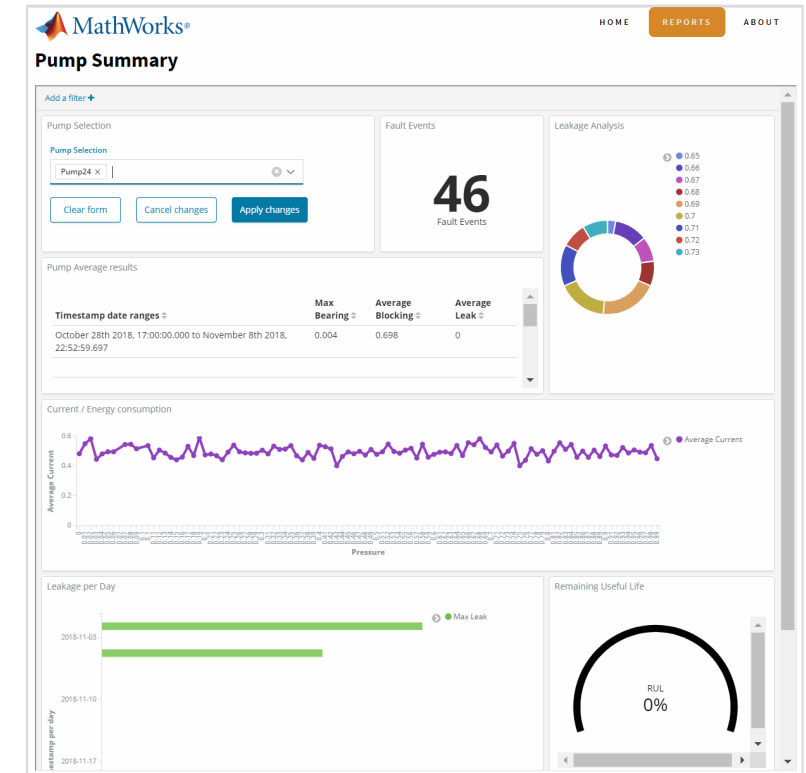
System Architect

Deploys and
operationalizes model
on Azure cloud



Operator

Makes operational
decisions based
on model output



Current system requires Operator to manually monitor operational metrics for anomalies. Their expertise is required to detect and take preventative action



Project statement: Develop end-to-end predictive maintenance system and demo in one 3-4 week sprint



Plant
Operator

1. Monitor *flow*, *pressure*, and *current* of each pump so I always know their *operational state*
2. Need *alert* when fault parameters drift outside an acceptable range so I can take *immediate corrective action*
3. Continuous estimate of each pump's *remaining useful life (RUL)* so I can *schedule maintenance or replace* the asset

Challenges of AI Deployment



Process
Engineer

We don't have a large set of failure data, and it's too costly to generate real failures in our plant for this project

Solution: Use an accurate physics-based software model for the pump to develop synthetic training sets



Challenges of AI Deployment



**System
Architect**

We don't have a large IT/hardware budget, and we need to see results before committing to a particular platform or technology

Solution: Leverage cloud platform to quickly configure and provision the services needed to build the solution, while minimizing lock-in to a particular provider

Challenges of AI Deployment



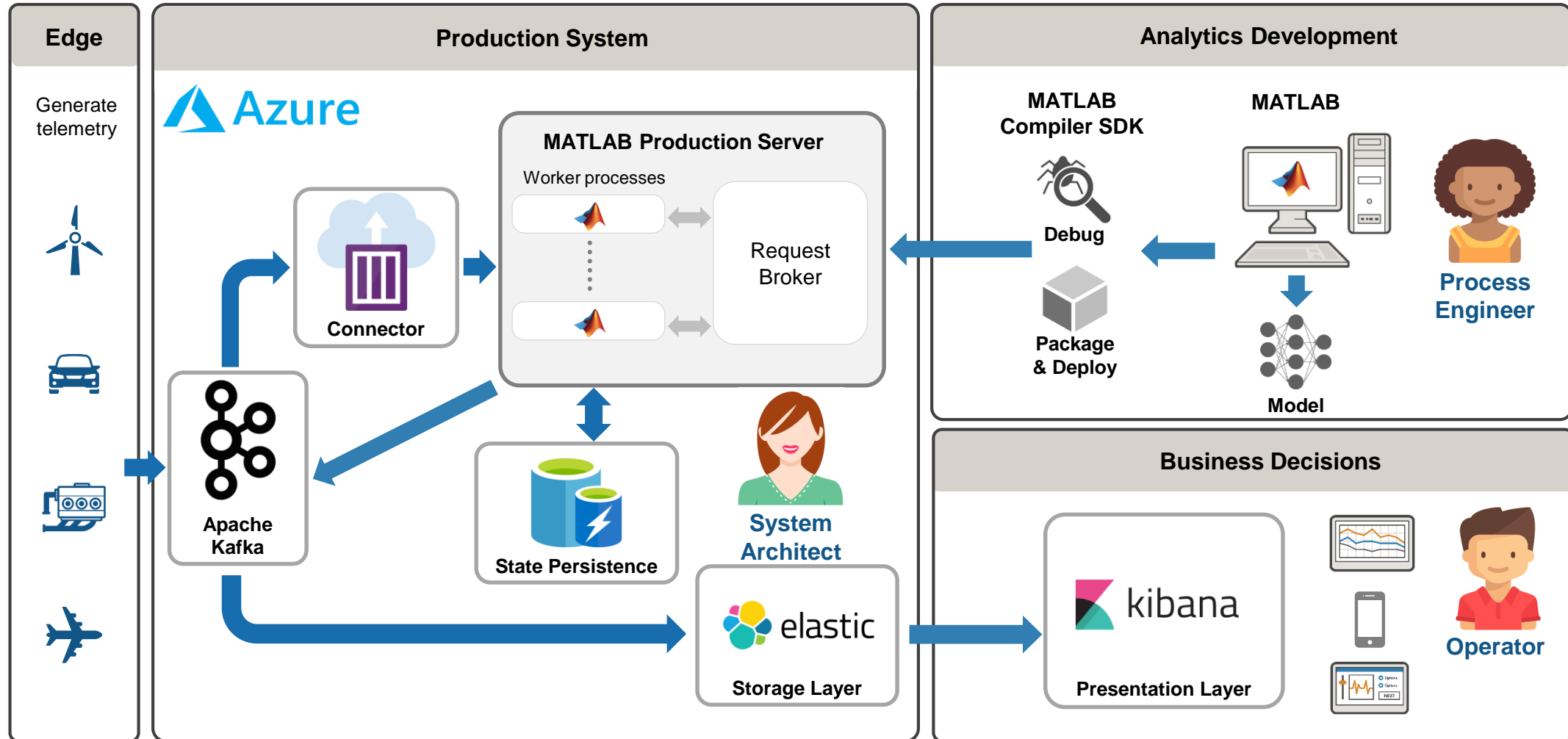
Process
Engineer

Need software for multidisciplinary problem across teams, plus integration with IT

Solution: Use MATLAB and integrate with Open Source Software



Predictive Maintenance Architecture on Azure





Modeling approach

Process Engineer

1

Access and Explore Data

Files



Databases



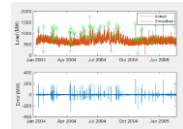
Sensors



2

Preprocess Data

Working with
Messy Data



Data Reduction/
Transformation



Feature
Extraction



3

Develop Predictive
Models

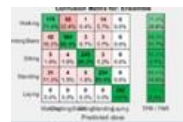
Model Creation e.g.
Machine Learning



Parameter
Optimization



Model
Validation



4

Integrate with
Production
Systems

Desktop Apps



Enterprise Scale
Systems



Embedded Devices
and Hardware



5

Visualize Results

3rd party
dashboards



Web apps





Process
Engineer

Review model requirements



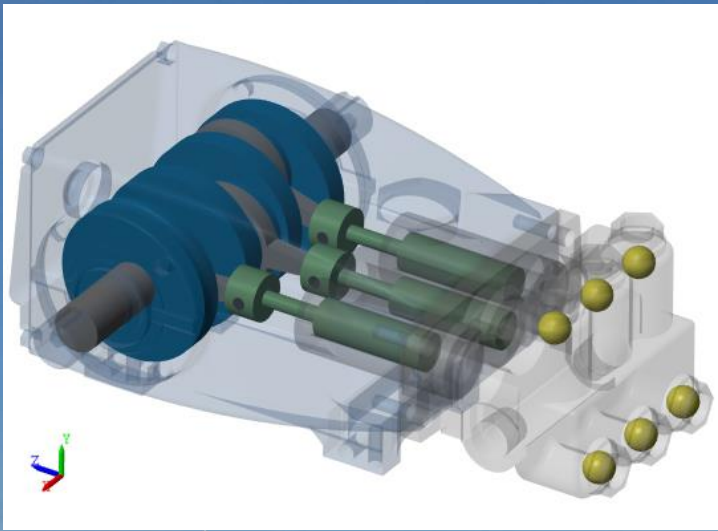
Requirements From Operator

- Continuous predictions of type of fault
 - “Blocking”
 - “Leaking”
 - “Bearing”
 - Combination of above
- Continuous predictions of Remaining Useful Life [RUL]



Requirements From System Architect

- Define window for streaming
- Define format of results, intermediate values
- Test code
- Scale code

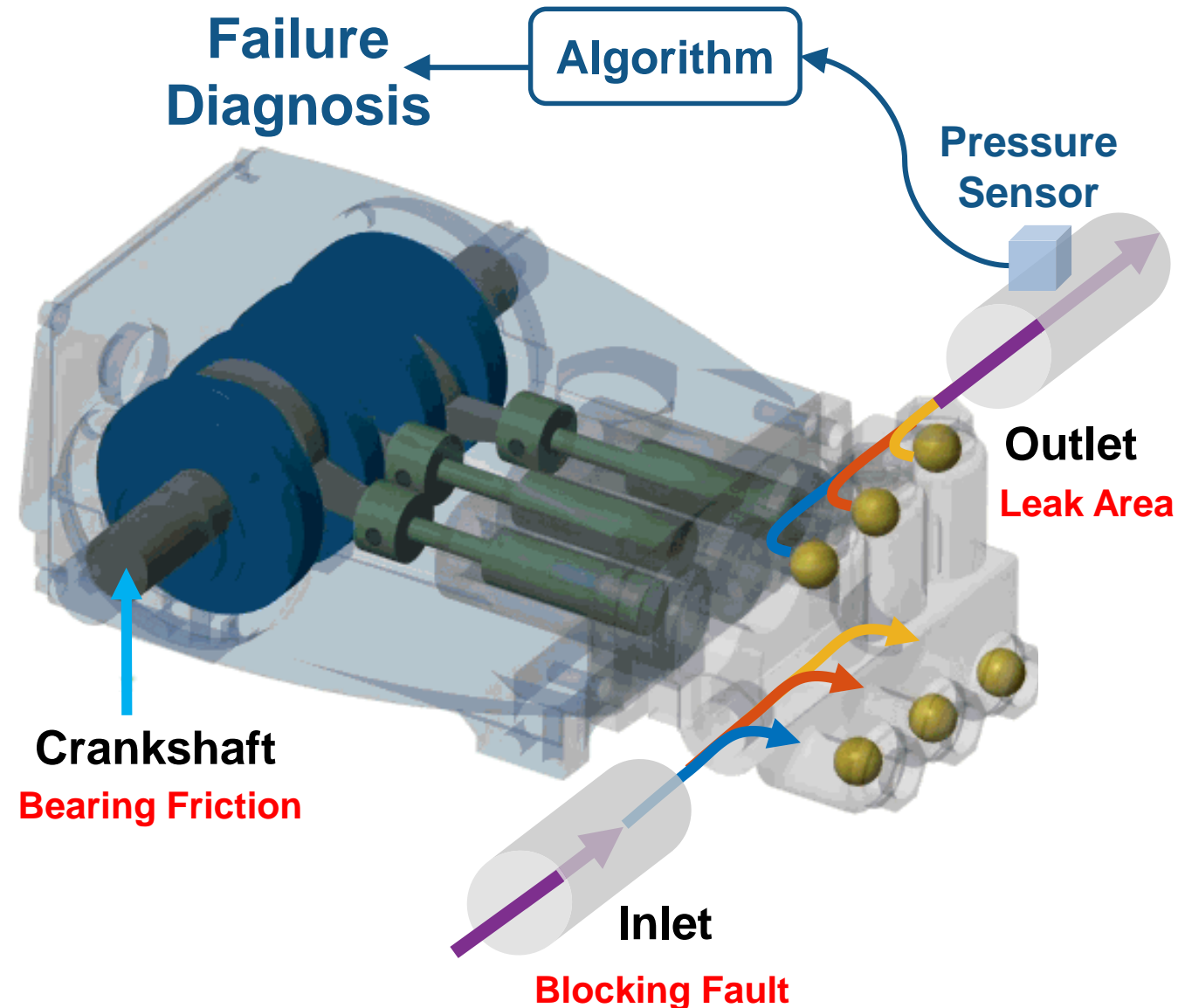
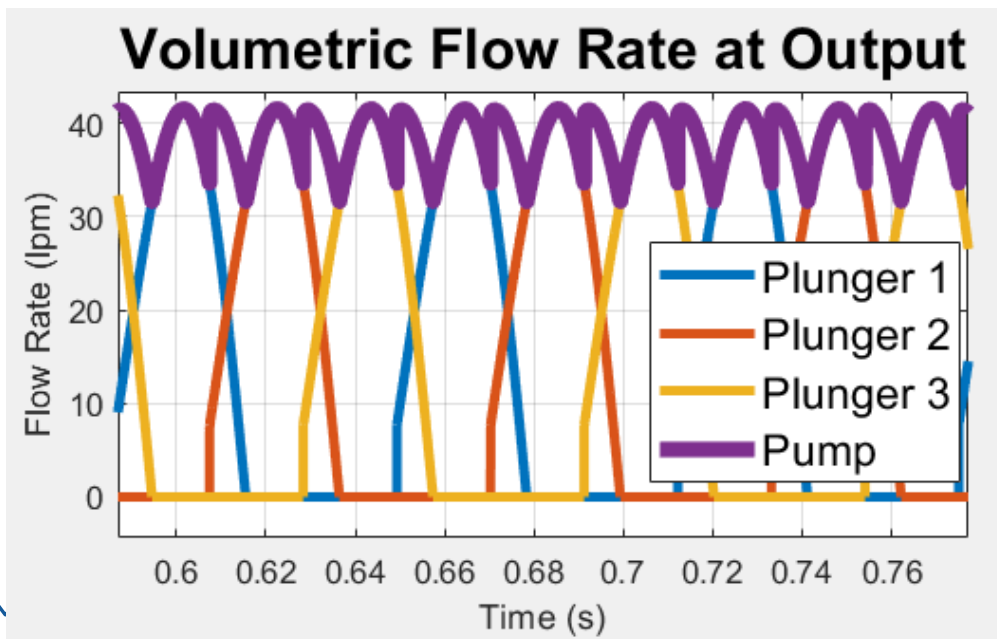




Process
Engineer

Physics of Triplex Pump

- Crankshaft drives three plungers
 - Each 120 degrees out of phase
 - One chamber always discharging
 - Three types of **failures**



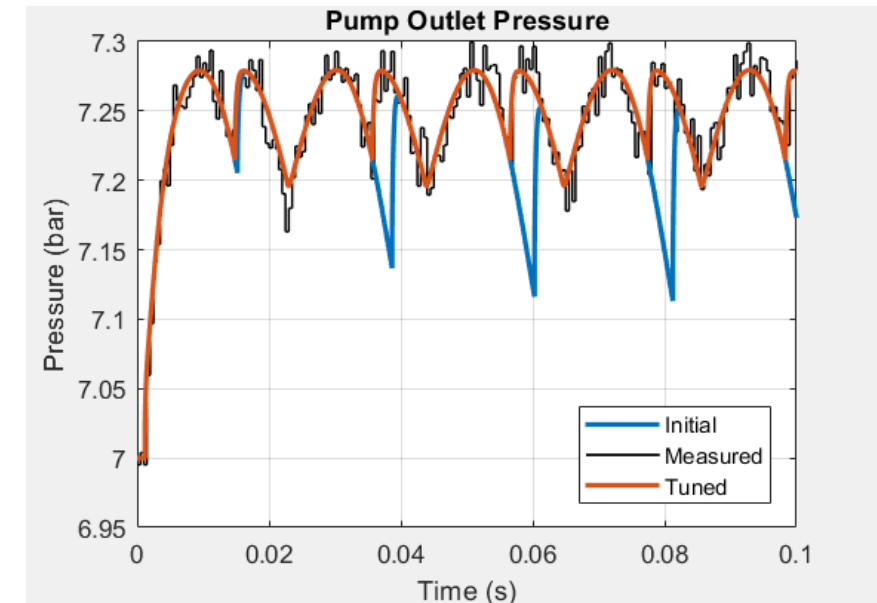
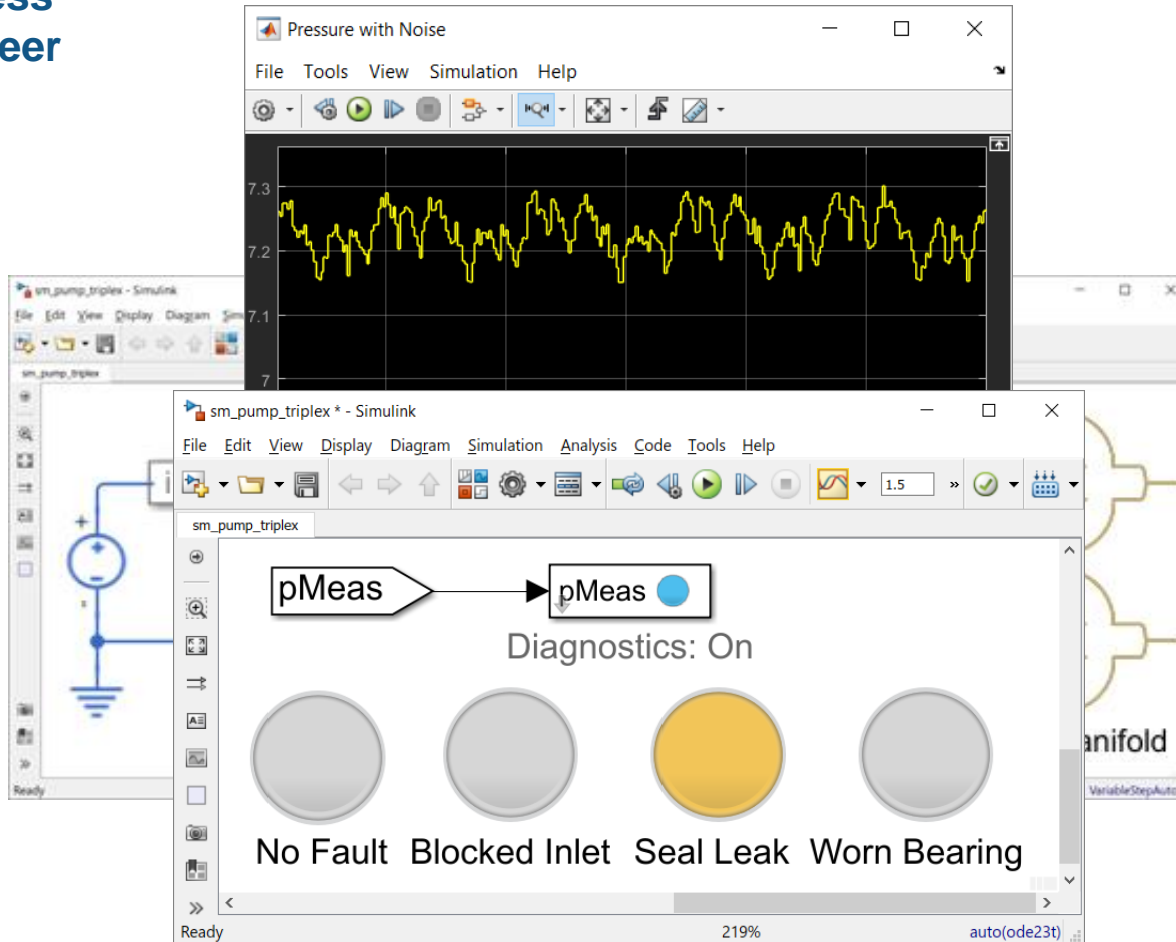


1

Access and Explore Data

Process
Engineer

Use sensor data from pump to identify levels of failure

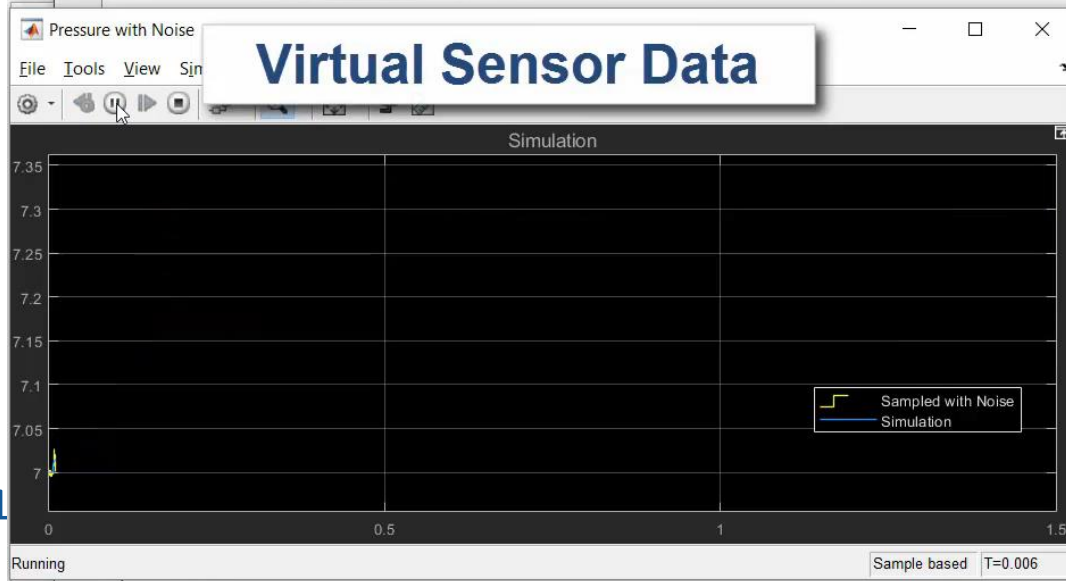
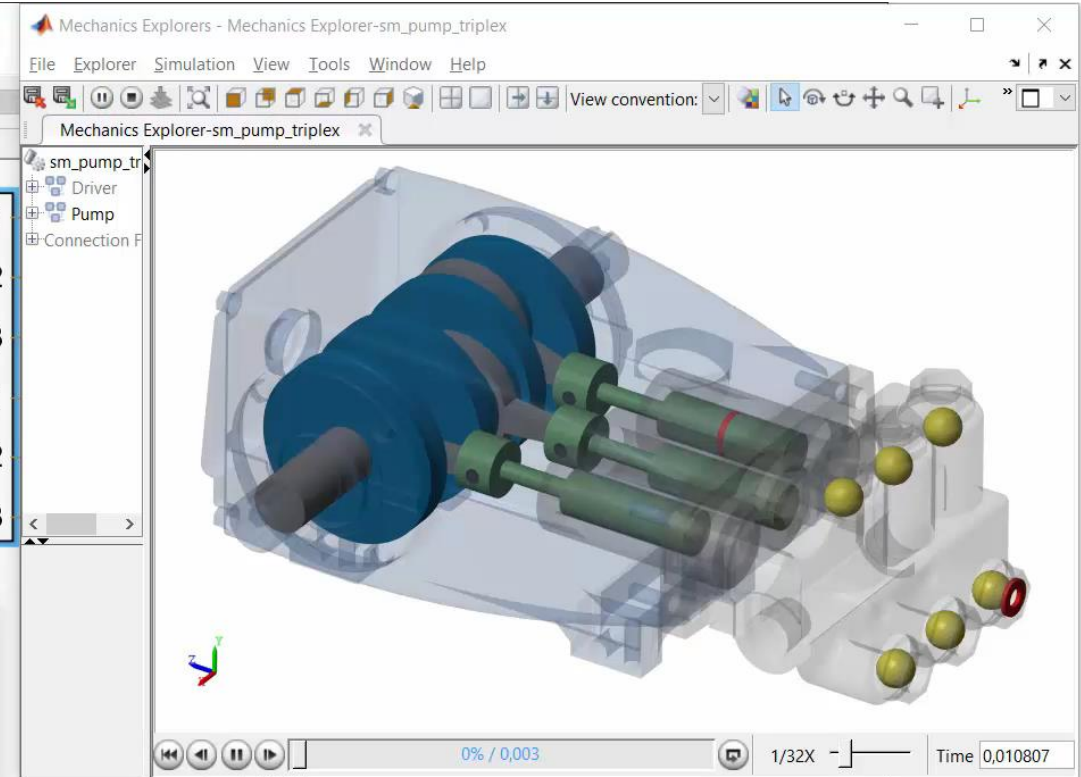
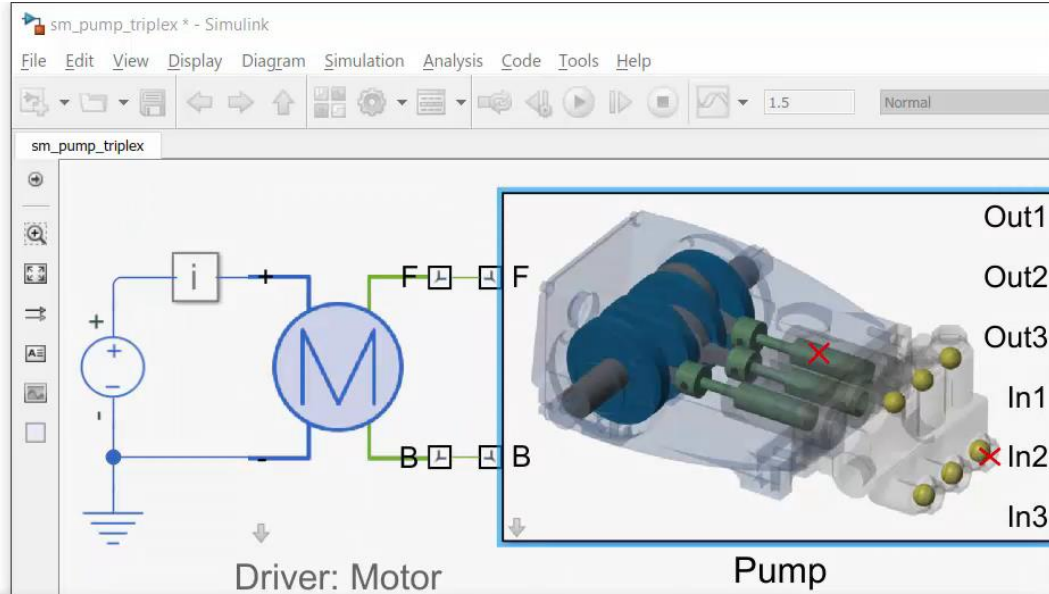




1

Access and Explore Data

Build digital twin and generate sensor data

Process
Engineer

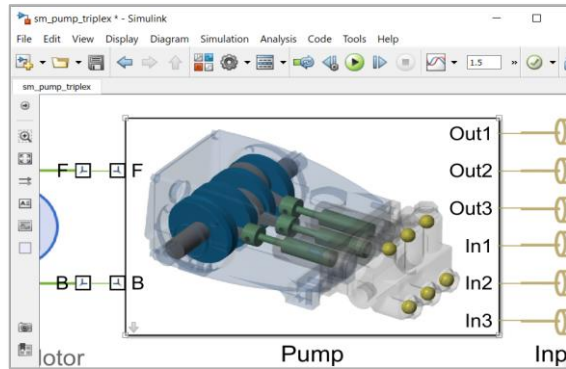


1

Access and Explore Data

Process
Engineer

Simulate data with many failure conditions

**Leak Area = [1e-9 0.036]****Bearing Friction = [0 6e-4]****Blocking Fault = [0.5 0.8]**

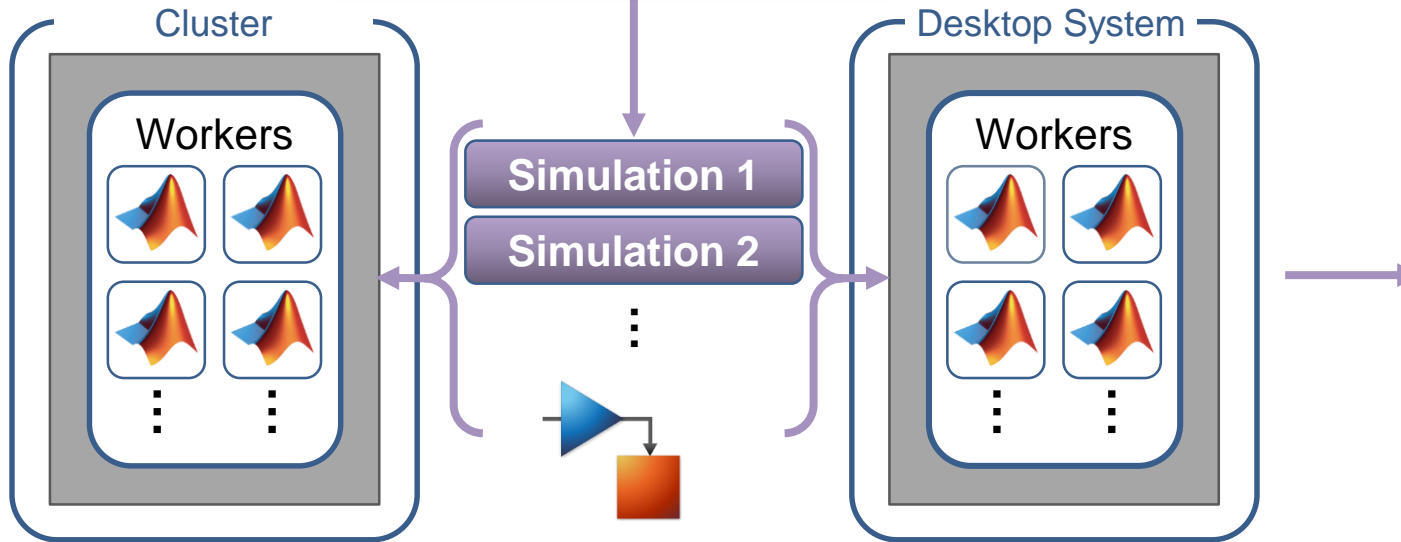
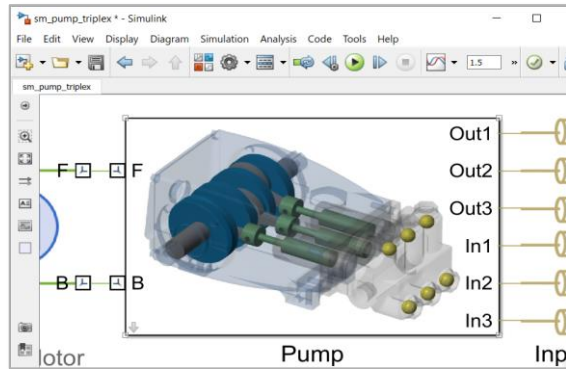


1

Access and Explore Data

Simulate data with many failure conditions

Process Engineer



Run parallel simulations

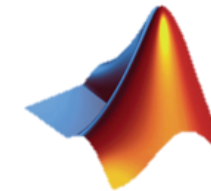
Access Data

```
ens = simulationEnsembleDatastore(location)
```

```
ens =
```

```
simulationEnsembleDatastore with properties:
```

```
DataVariables: [25x1 string]
IndependentVariables: [0x0 string]
ConditionVariables: [0x0 string]
SelectedVariables: [25x1 string]
ReadSize: 1
NumMembers: 702
LastMemberRead: [0x0 string]
Files: [702x1 string]
```



Store data on HDFS



2

Preprocess Data

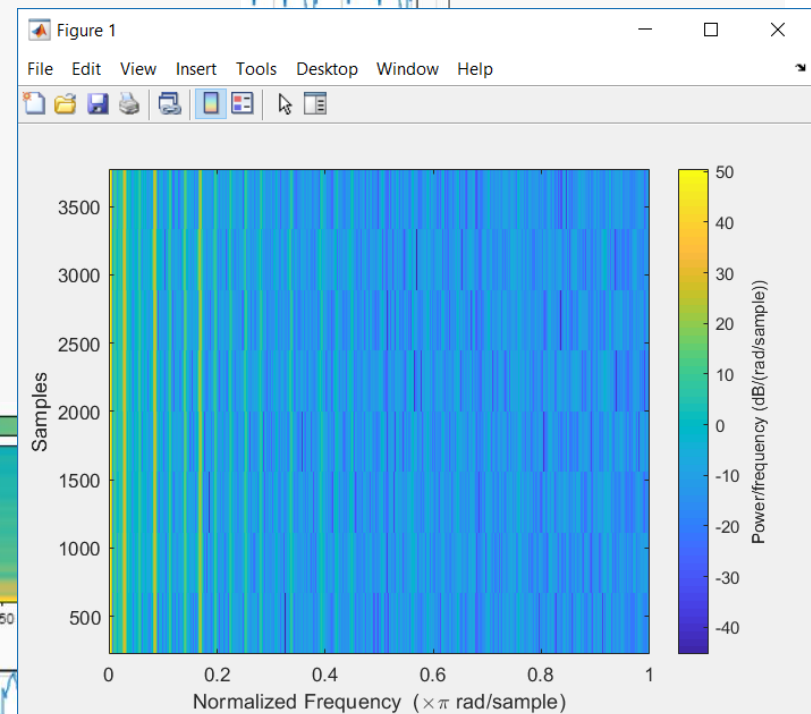
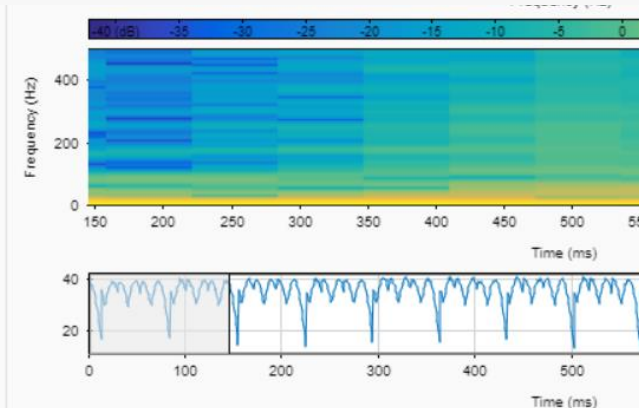
Represent signal information

Process
Engineer

Signal processing

```
[Spectrum,Frequencies] = pspectrum(data.Flow);
[pLow,pHigh] = bounds(Spectrum);
fPeak = Frequencies(Spectrum==pHigh);
qPeak2Peak = peak2peak(data.Flow);
qCrest = peak2rms(data.Flow);
qRMS = rms(data.Flow);
qMAD = mad(data.Flow);
```

NAME	SIZE	CLASS
allfaults	1000×3	timetable
bearingPump	1000×3	timetable
blockedPu...	1000×3	timetable
healthyPump	1000×3	timetable
leakingPump	1000×3	timetable





3

Develop Predictive Models

Process Engineer

Develop Predictive Models in MATLAB

	Time	1 LeakFault	2 BlockingFault	3 BearingFault	4 FaultType
1	0 sec	2.8472	-0.1477	1.8000	All
2	0.001 sec	-0.1498	-0.4207	1.3103	Bearing & Blocking
3	0.002 sec	0.6511	1.6521	-0.5557	Leak
4	0.003 sec	0.1469	-0.2775	1.0074	All
5	0.004 sec	-0.6480	0.7065	-0.8878	Blocking
6	0.005 sec	-0.8165	-0.5434	-0.3079	Blocking
7	0.006 sec	-1.0061	1.2083	0.0661	Bearing
8	0.007 sec	1.0125	-1.9098	-0.7027	Leak & Blocking

Label Faults

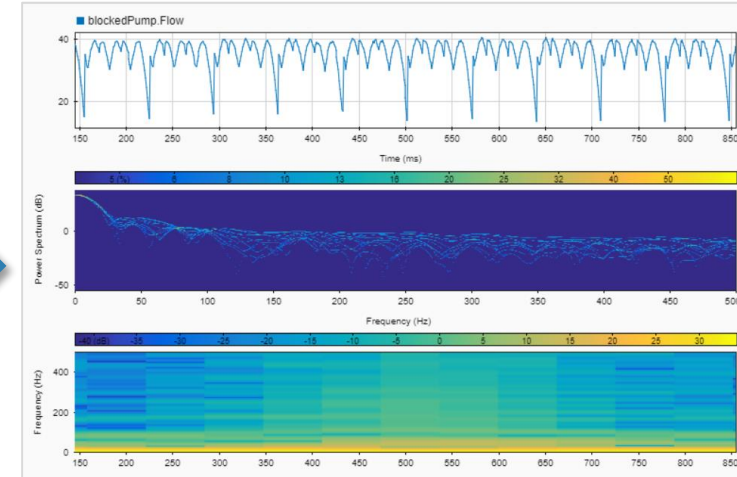
Scale

```
tt = tall(ds);
tt = preprocessData(tt);
model = TreeBagger(50,tt,'Event');
```

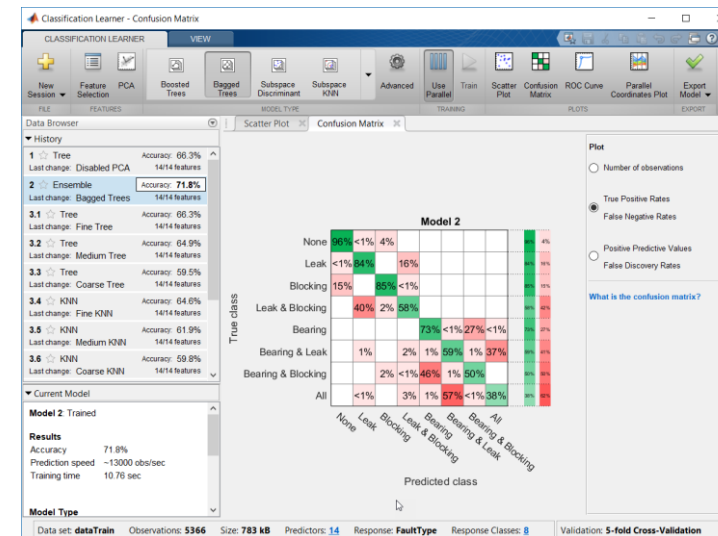
Evaluating tall expression using the Spark Cluster:

- Pass 1 of 2: Completed in 11 sec
- Pass 2 of 2: Completed in 2.3333 min

Evaluation completed in 2.6167 min



Represent Signals



Train Model

Validate Model

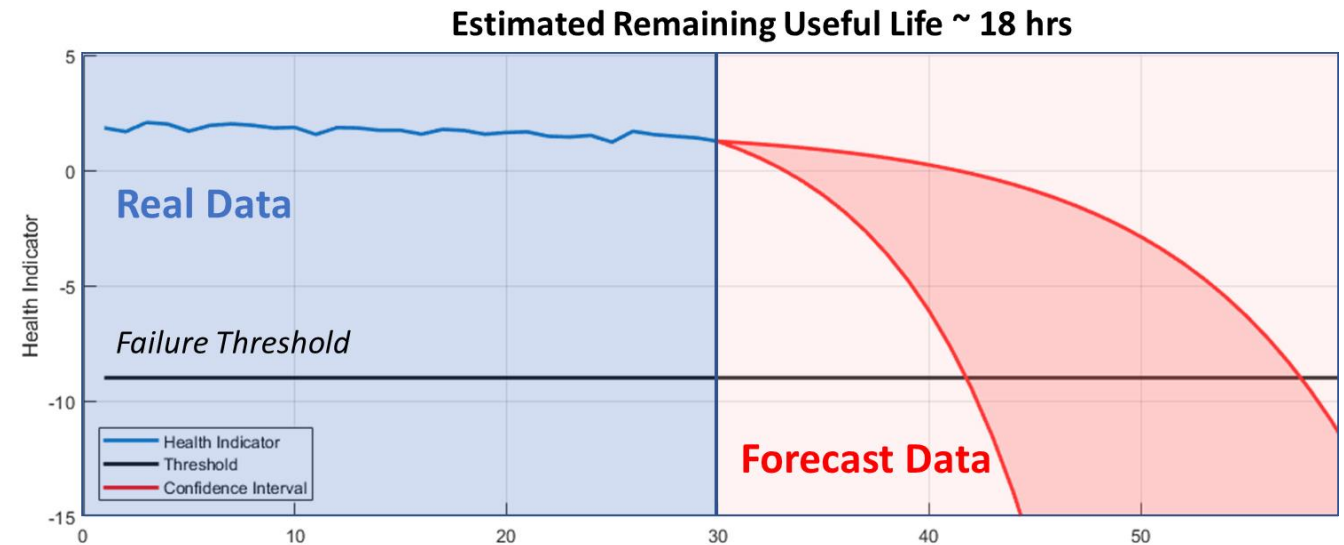
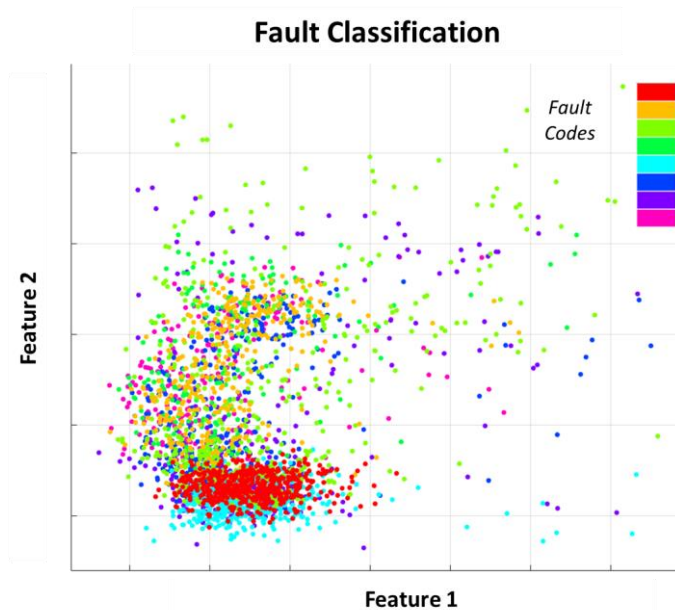


3

Develop Predictive Models

Process Engineer

Develop Predictive Models in MATLAB



**Type of Fault
(Classification)**

**Remaining Useful Life
(Regression)**



Plant Operator

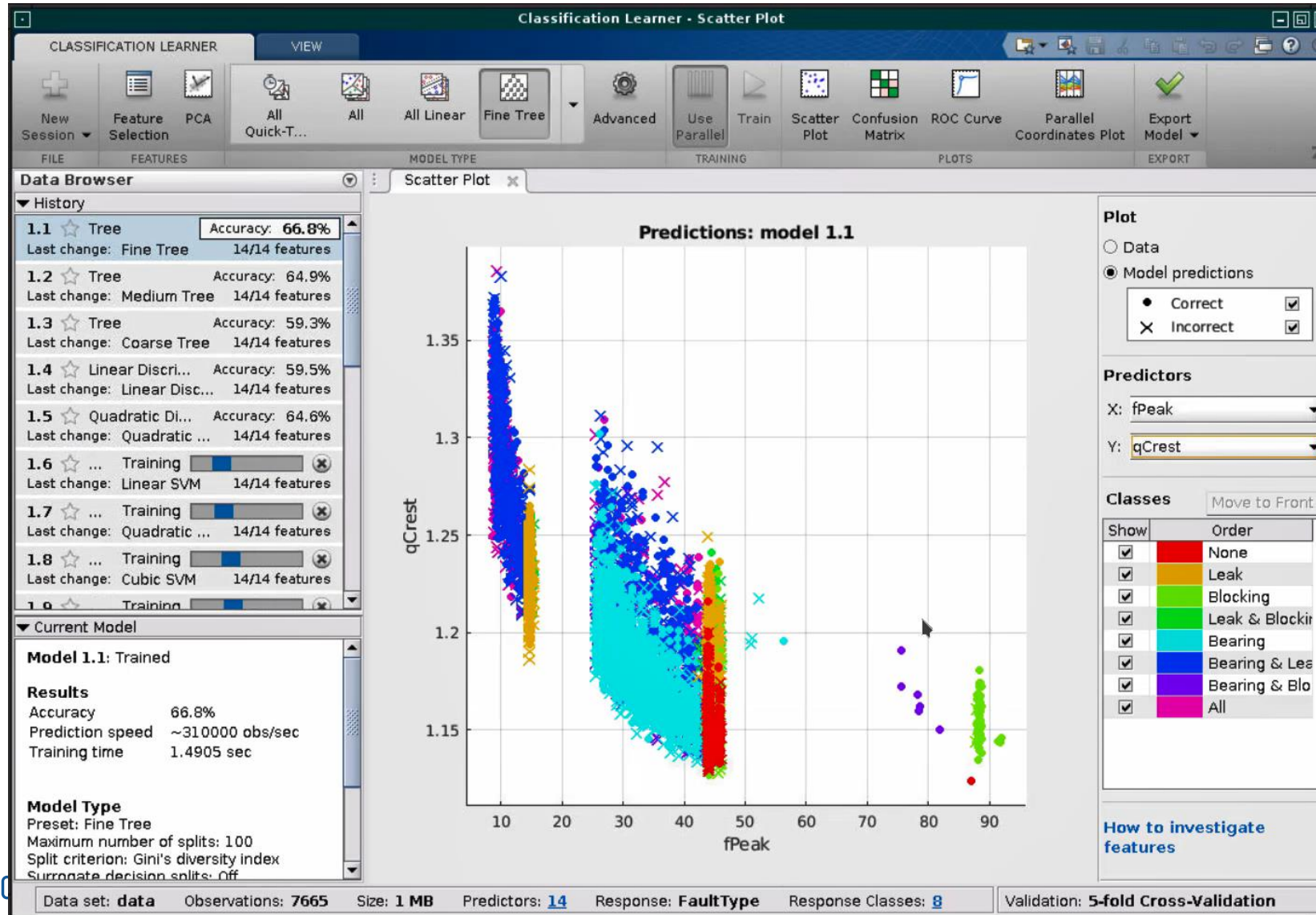


3

Develop Predictive Models

Process Engineer

Develop Machine Learning Models



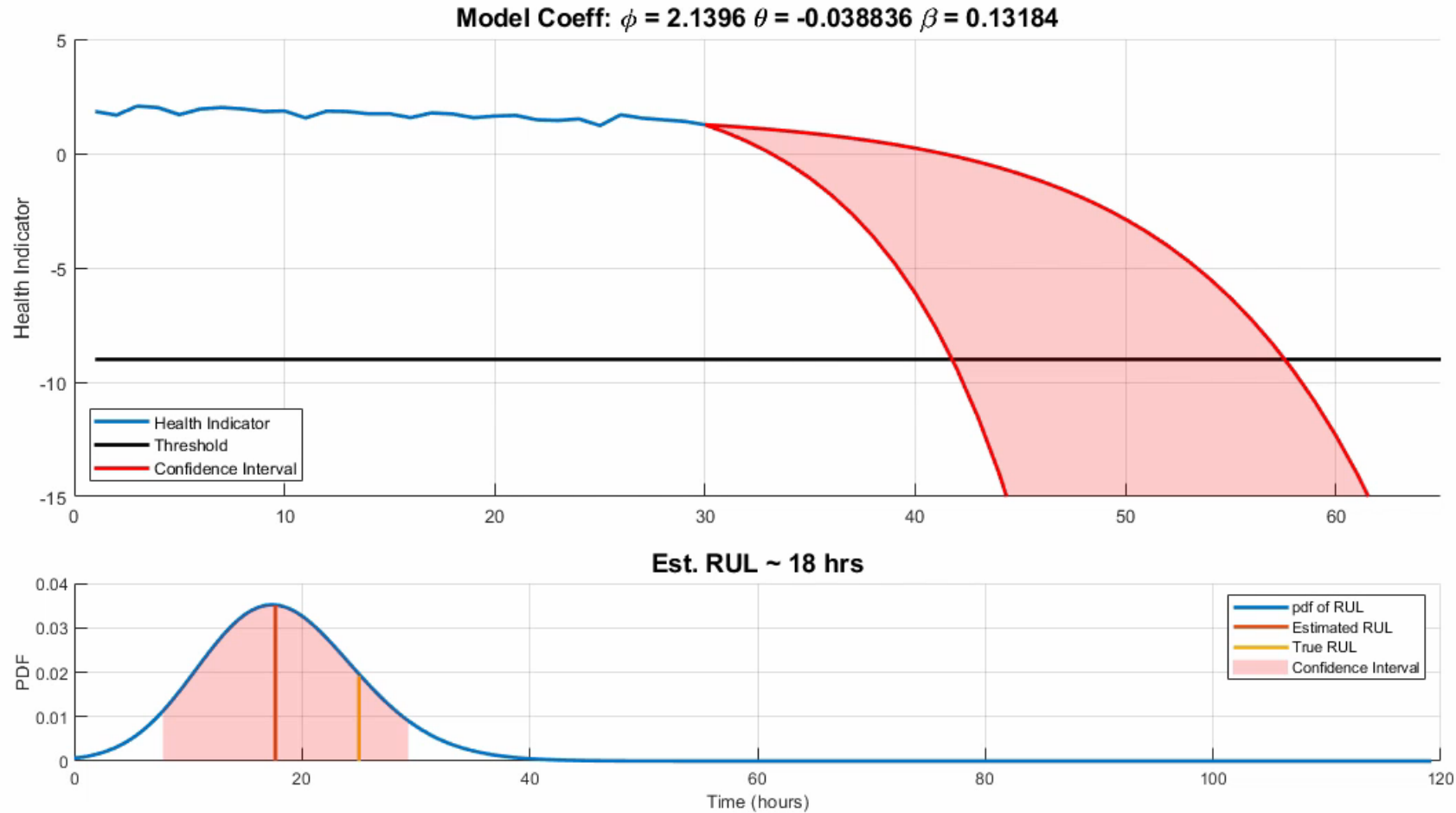


3

Develop Predictive Models

Process Engineer

Estimate Remaining Useful Life



$$S(t) = \phi + \theta(t) e^{(\beta(t)t + \epsilon(t) - \frac{\sigma}{2})}$$



4

Integrate with
Production
Systems

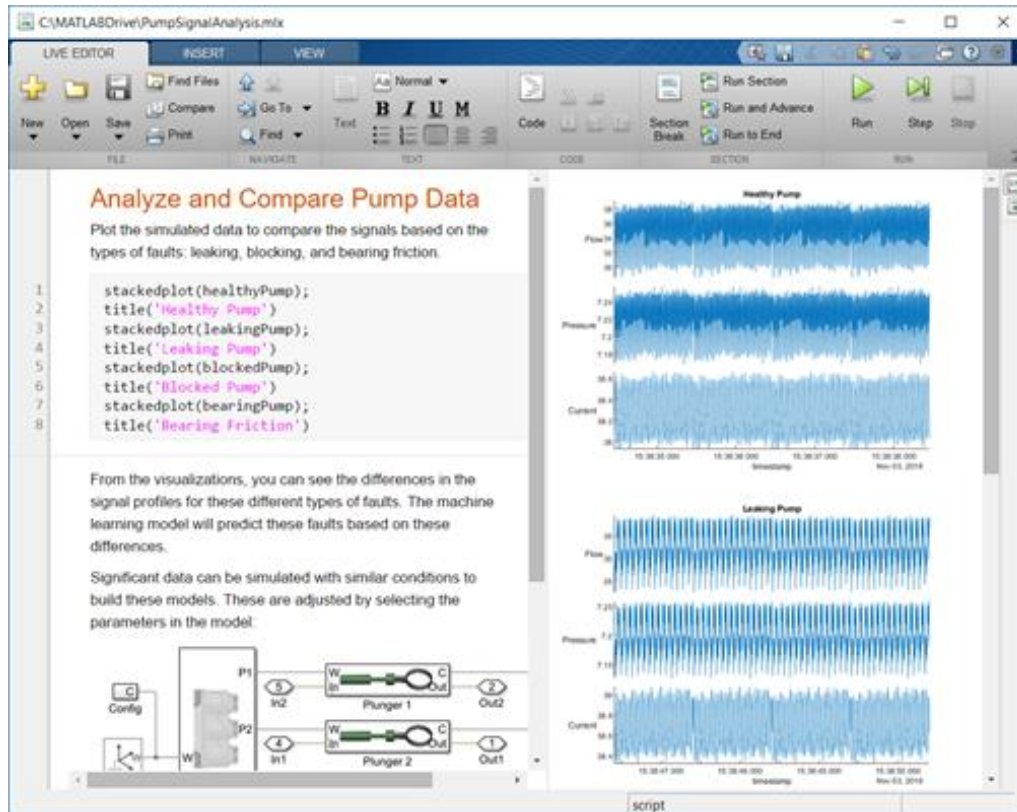
Process
Engineer

Share with the team

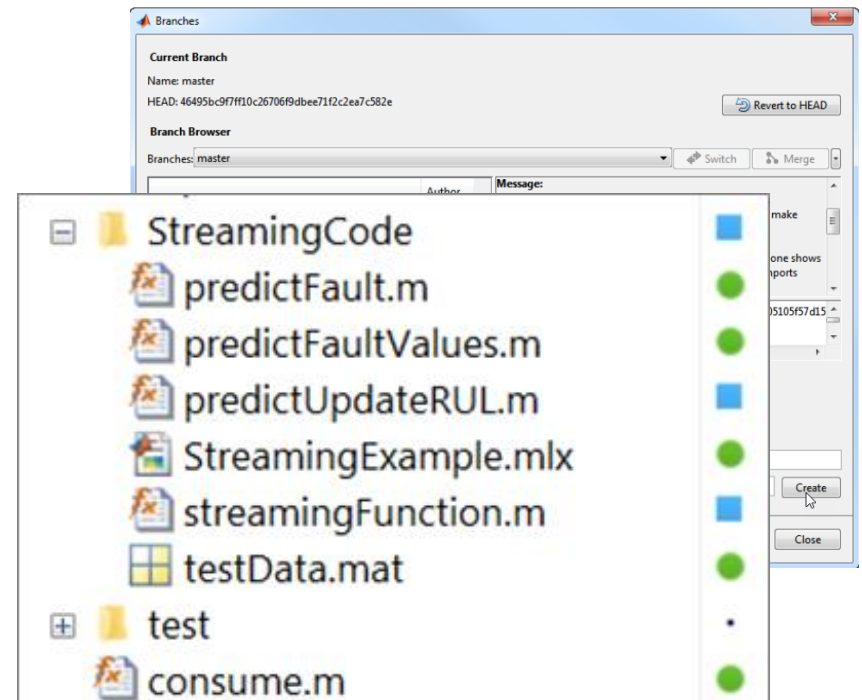
Review results with
Operator



Share code with
System Architect



.pdf, html, LaTeX



Source Control

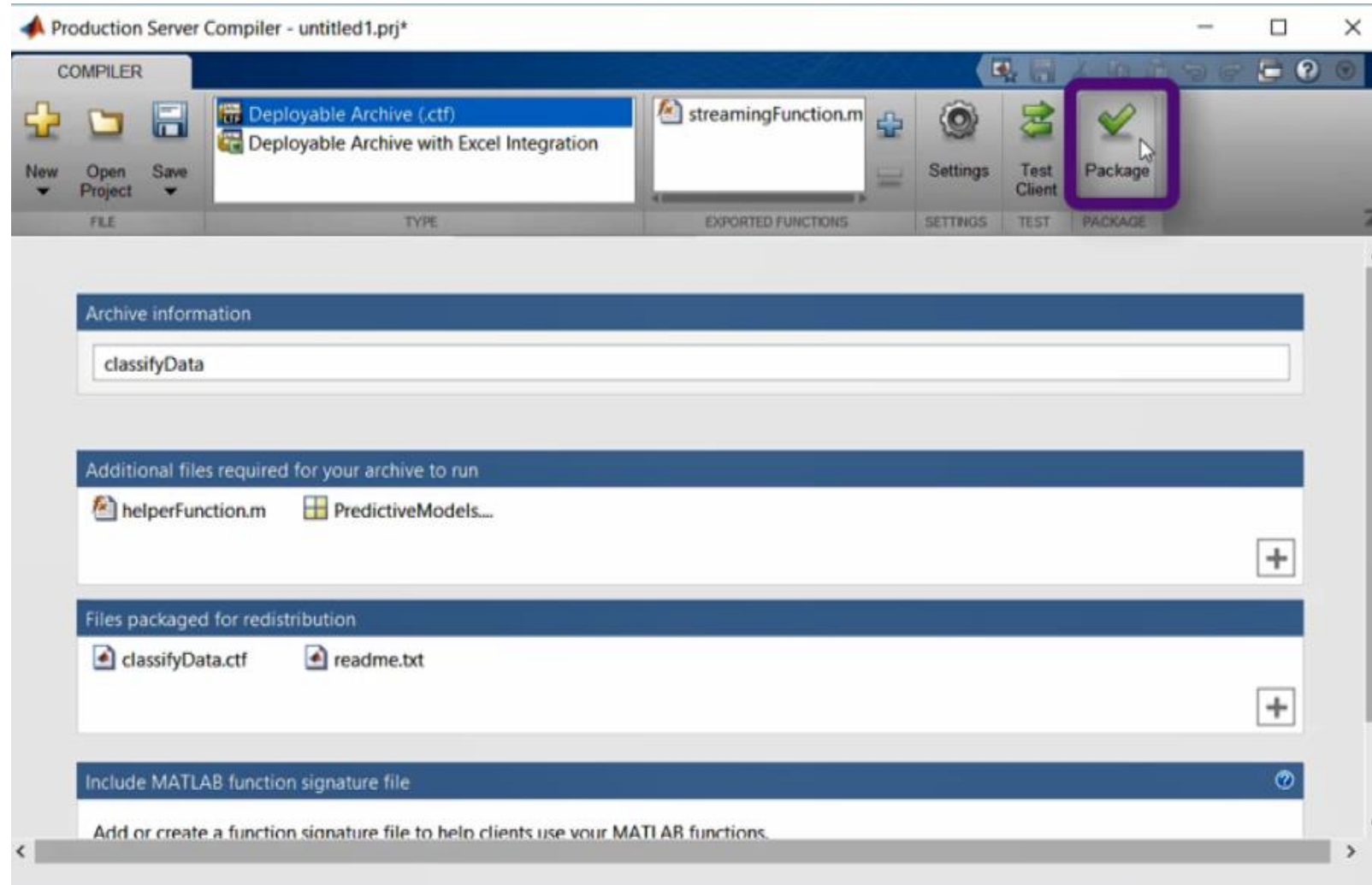


4

Integrate with
Production
Systems

Process
Engineer

Package Stream Processing Function





4

Integrate with
Production
Systems

Review System Requirements

- Requirements from the Process Engineer
 - Every millisecond, each pump generates a time-stamped record of flow, pressure, and current
 - Model expects 1 sec. window of data per pump
 - Initially, 1's – 10's of devices, but quickly scale to 100's
- Requirements from the Operator
 - Alerts when parameters drift outside the expected ranges
 - Continuous estimating of RUL for each pump



Process Engineer



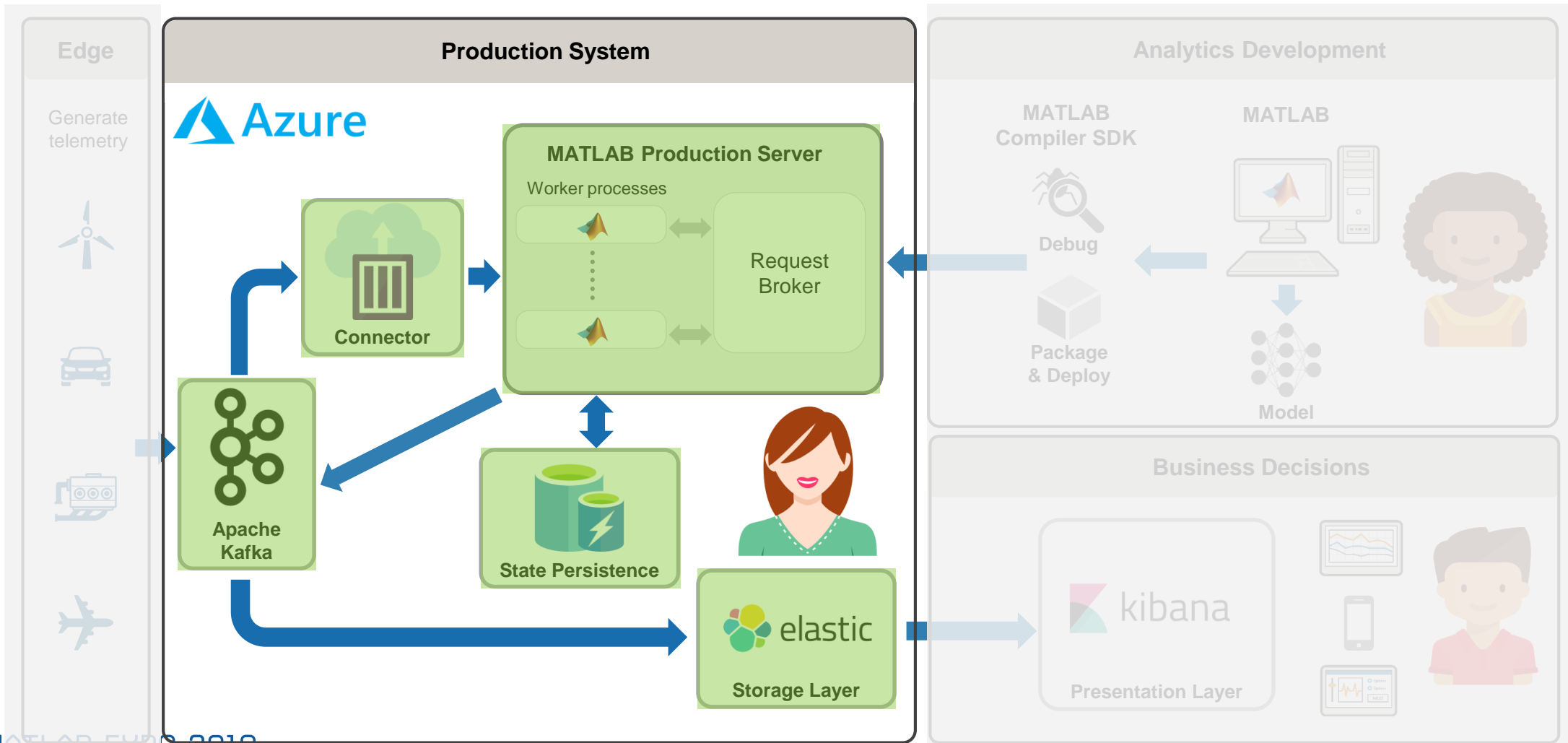
Operator



4

**Integrate with
Production
Systems**

Integrate Analytics with Production Systems





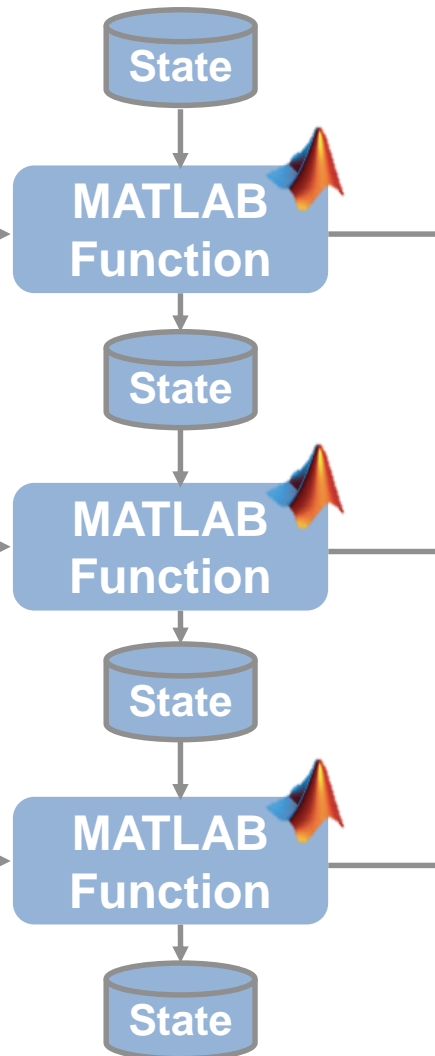
4

Integrate with
Production
Systems

Streaming data is treated as an unbounded Timetable

Input Stream

Event Time	Pump Id	Flow	Pressure	Current
18:01:10	Pump1	1975	100	110
18:10:30	Pump3	2000	109	115
18:05:20	Pump1	1980	105	105
18:10:45	Pump2	2100	110	100
18:30:10	Pump4	2000	100	110
18:35:20	Pump4	1960	103	105
18:20:40	Pump3	1970	112	104
18:39:30	Pump4	2100	105	110
18:30:00	Pump3	1980	110	113
18:30:50	Pump3	2000	100	110
...



Output Stream

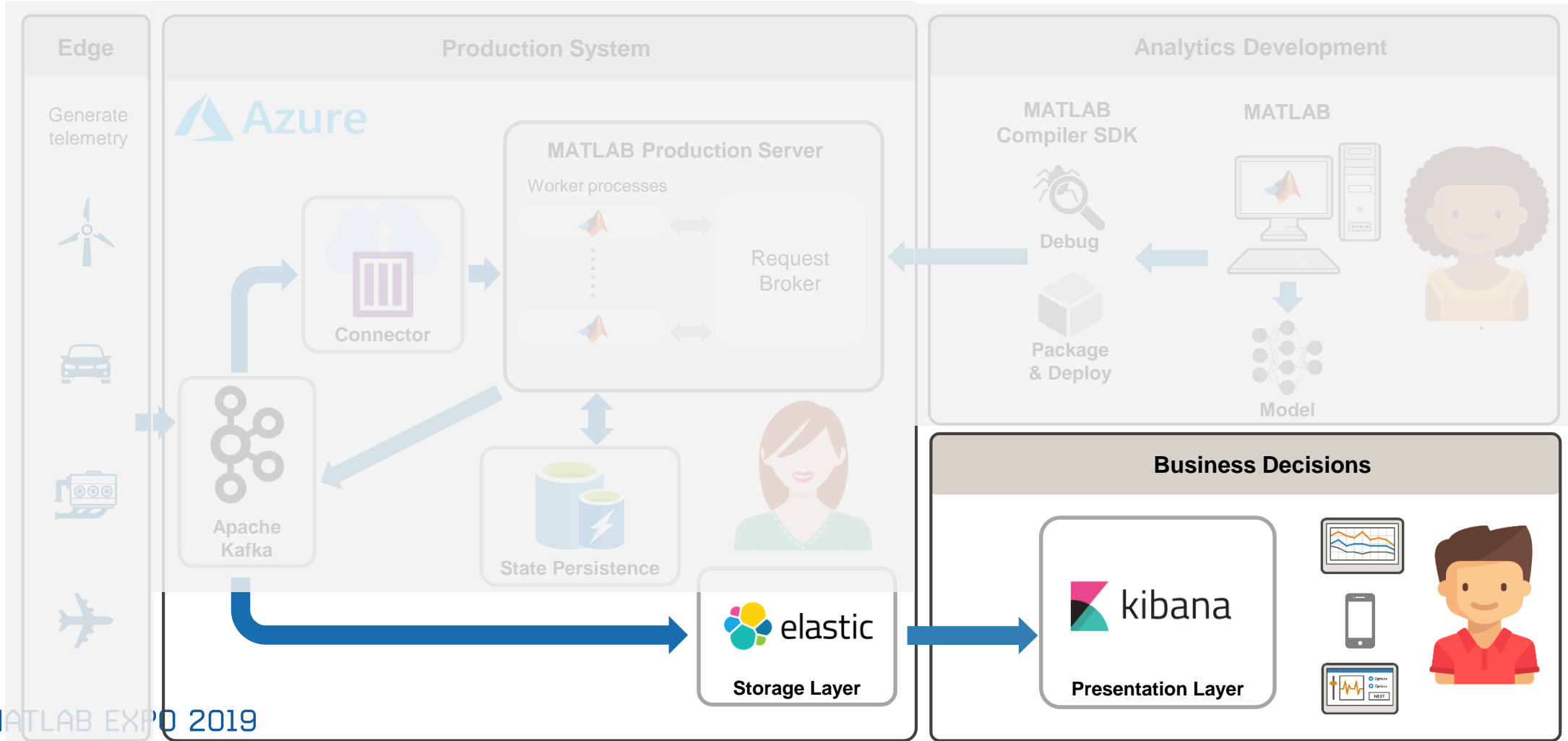
Time window	Pump Id	Bearing Friction
...
18:00:00	18:10:00	Pump1 Pump3 Pump4
18:10:00	18:20:00	Pump2 Pump3 Pump4
18:20:00	18:30:00	Pump1 Pump3 Pump4
18:30:00	18:40:00	Pump5 Pump3 Pump4



4

**Integrate with
Production
Systems**

Complete your application



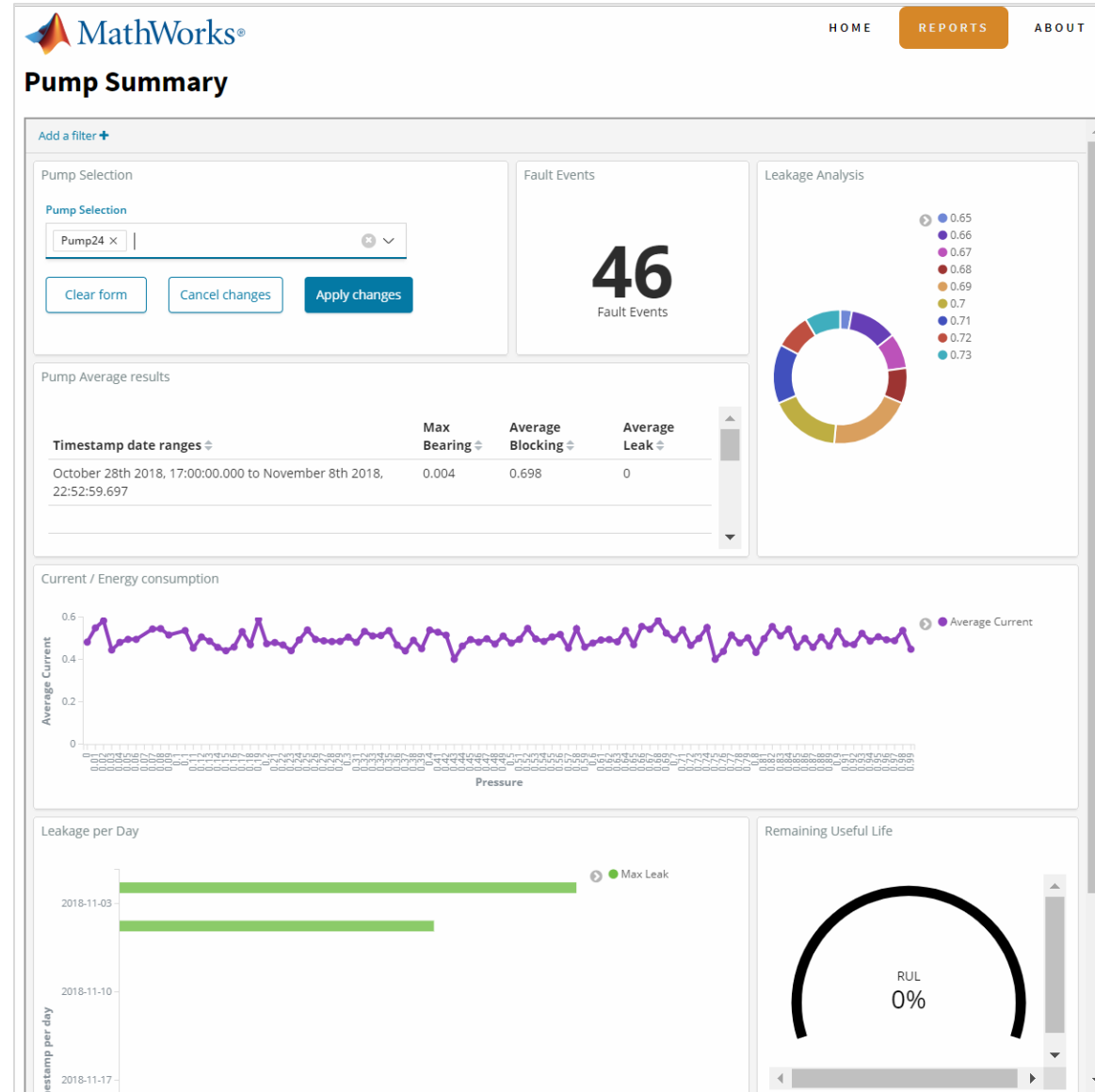


5

Visualize Results

Plant
Operator

Complete Your Application



Team Retrospective

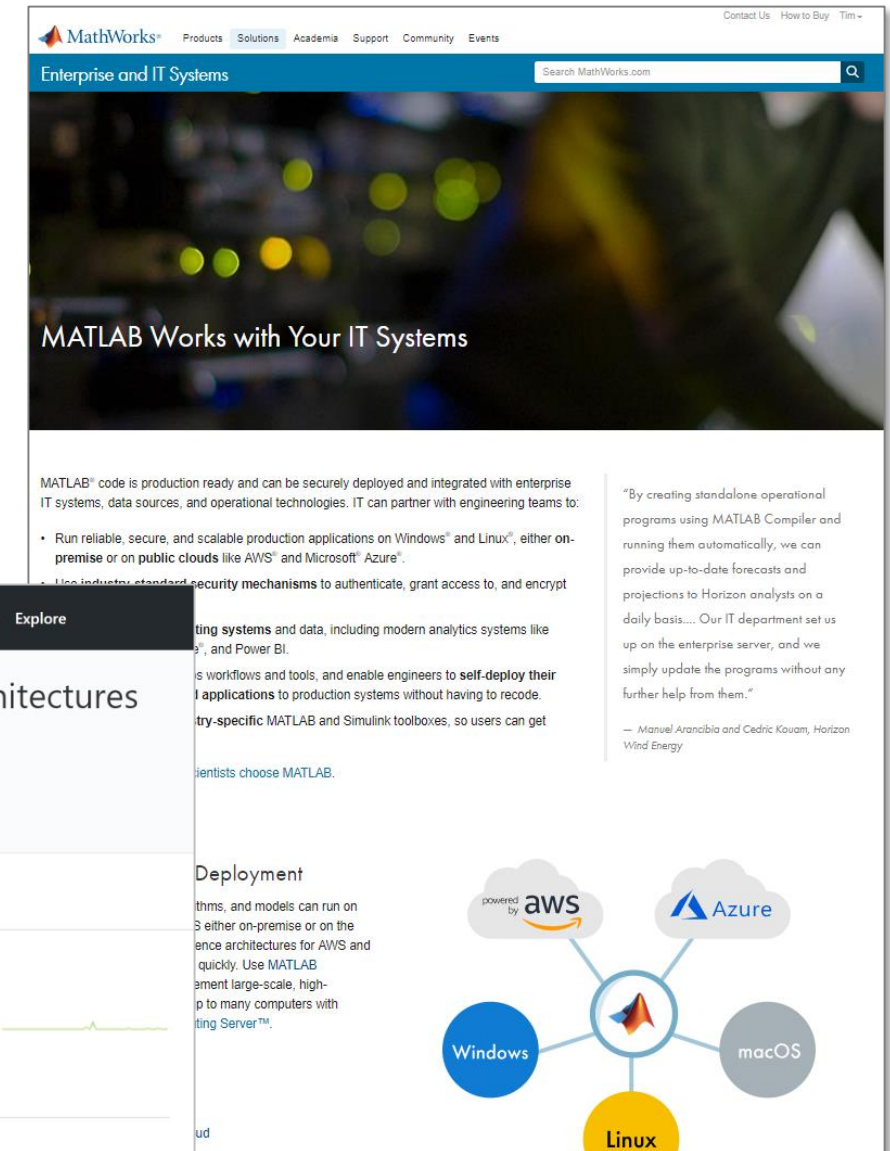
- Completed demo of full system in 3 week sprint
- Successfully used digital twin to generate faults and train models
- Fast prototyping of physical and AI models with MATLAB and Simulink.
Easy integration with OSS
- Cloud platform enabled faster IT setup

Takeaways

- You will face streaming data at some point
- Infrastructure may vary - MATLAB is always there
- Large or Small data, the concepts are the same
- Talk to us: www.mathworks.com

Resources to learn and get started

- [GitHub: MathWorks Reference Architectures](#)
- [Working with Enterprise IT Systems](#)
- [Data Analytics with MATLAB](#)
- [Simulink](#)



The image shows two overlapping screenshots. The background screenshot is the MathWorks website, specifically the 'Enterprise and IT Systems' section. It features a dark header with navigation links (Products, Solutions, Academia, Support, Community, Events) and a search bar. Below the header is a large banner with the text 'MATLAB Works with Your IT Systems'. The foreground screenshot is a GitHub repository page titled 'MathWorks Reference Architectures'. It shows the repository name, a verified link to 'https://mathworks.com/cloud', and a list of repositories. Two repositories are visible: 'mdcs-on-azure' and 'mps-on-aws'. The 'mdcs-on-azure' repository is highlighted, showing its description: 'Stand up a MATLAB Distributed Computing Server cluster using Azure Deployment'. To the right of the GitHub page, there is a diagram titled 'Deployment' showing a central MATLAB logo connected to four cloud providers: AWS, Azure, Windows, and macOS. The Linux logo is also present at the bottom.