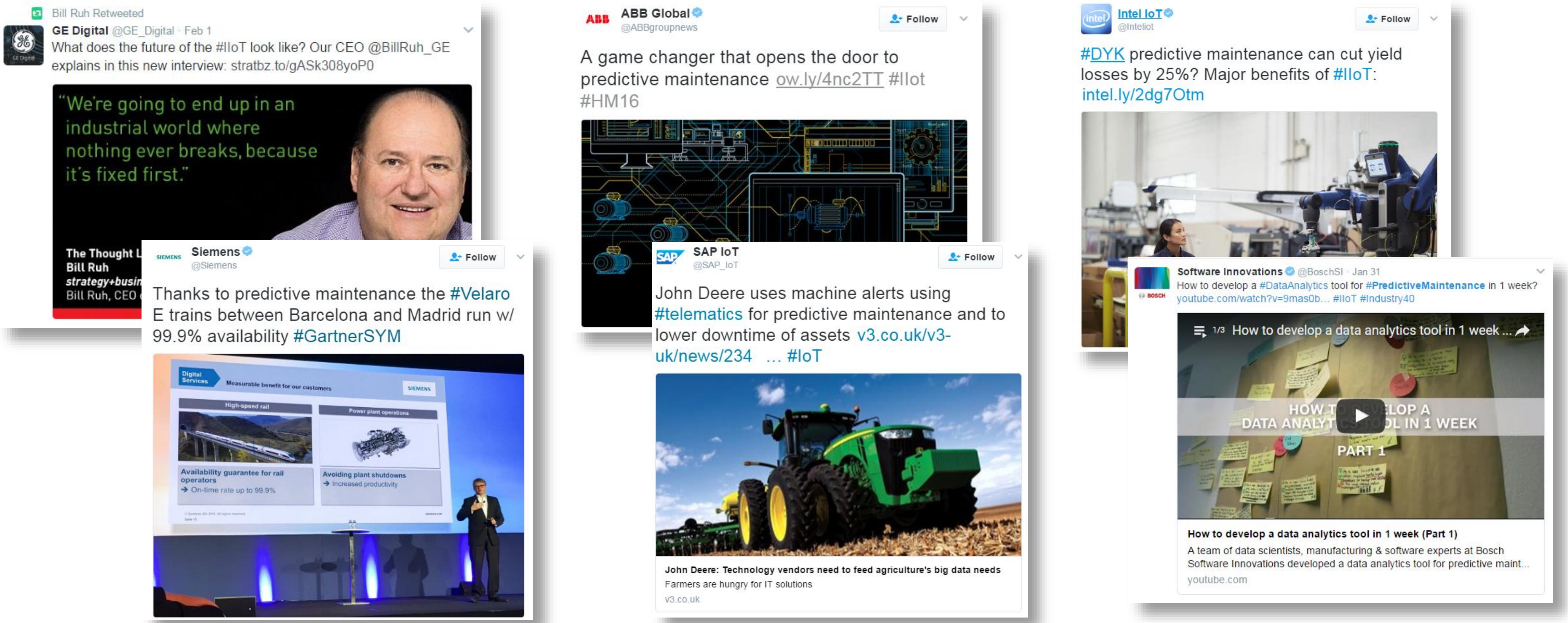
# Predictive Maintenance with MATLAB and Simulink

**Alec Stothert**
**Development Manager**
**Design Optimization and Identification**

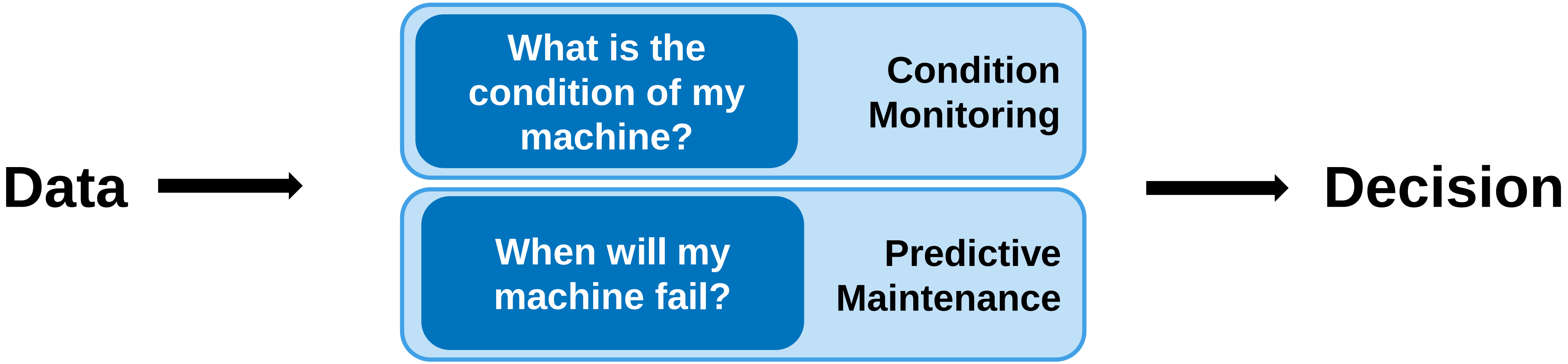
# Why Predictive Maintenance?

- Improved operating efficiency
- New revenue streams
- Competitive differentiator



# What does a Predictive Maintenance algorithm do?

**Helps make maintenance decisions based on large volumes of complex data**



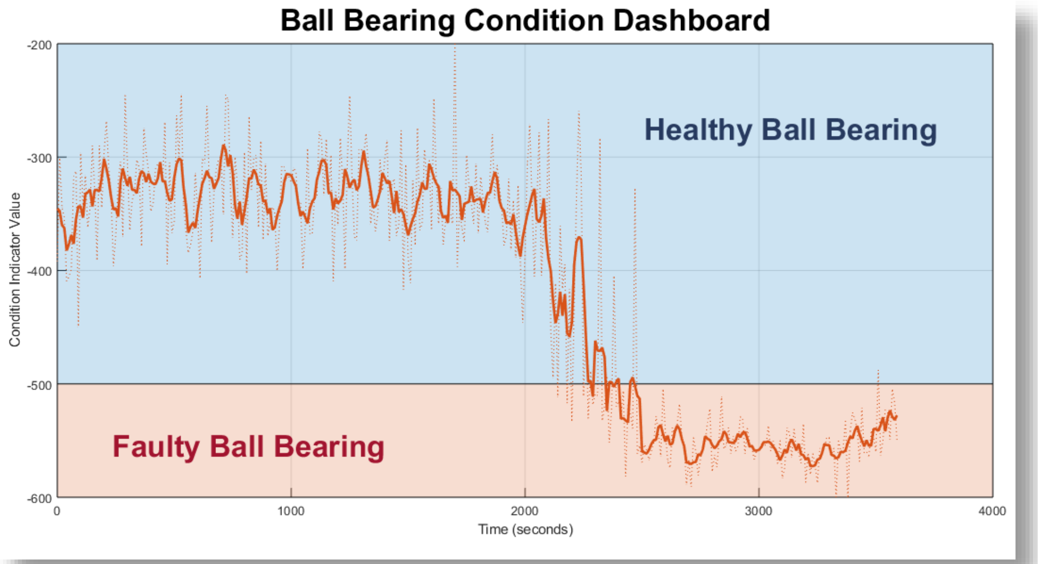

**Condition Monitoring**
Process of monitoring sensor data from machines (vibration, temperature etc.) in order to identify significant changes which can indicate developing faults

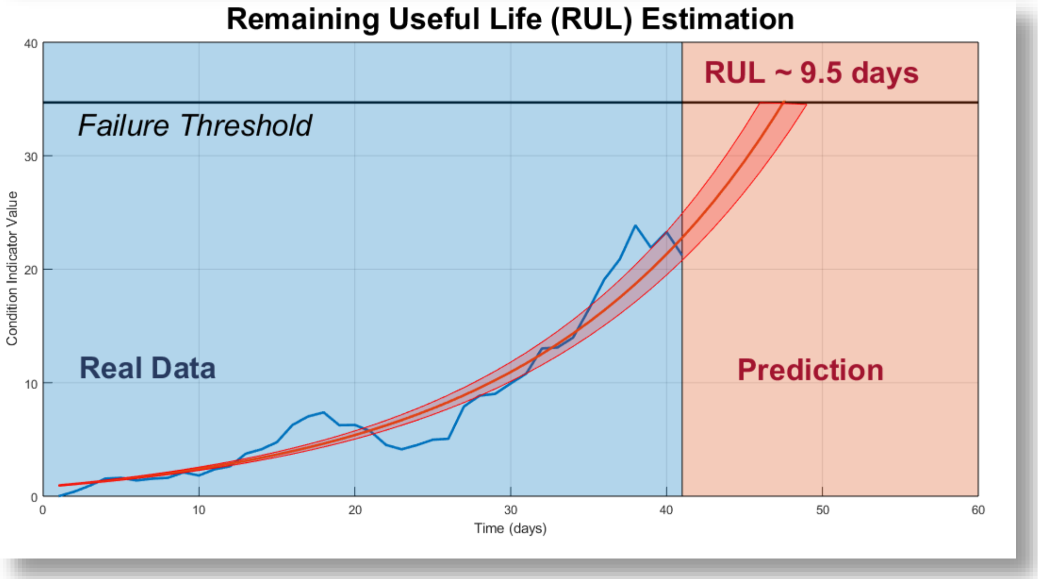
**Predictive Maintenance**
Technique that determines **time-to-failure/remaining useful life (RUL)** from sensor data & historical data in order to predict when maintenance should be performed

# Predictive Maintenance Toolbox

R2018a

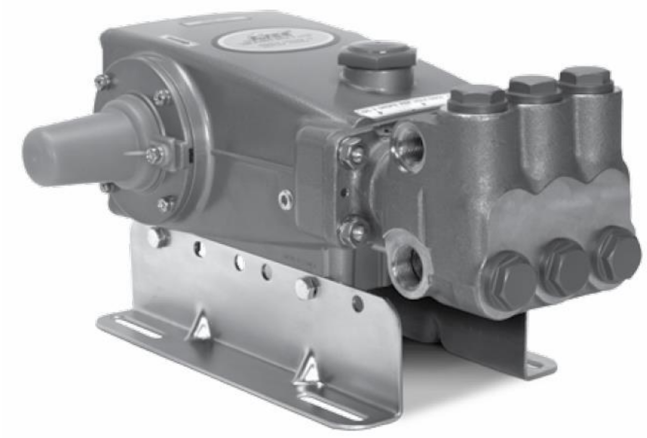
- Develop and validate condition monitoring and predictive maintenance algorithms
- Apply signal processing and dynamic modeling techniques to extract features from your data to monitor machine health
- Train machine learning and time-series models to detect, classify, and predict machine failure



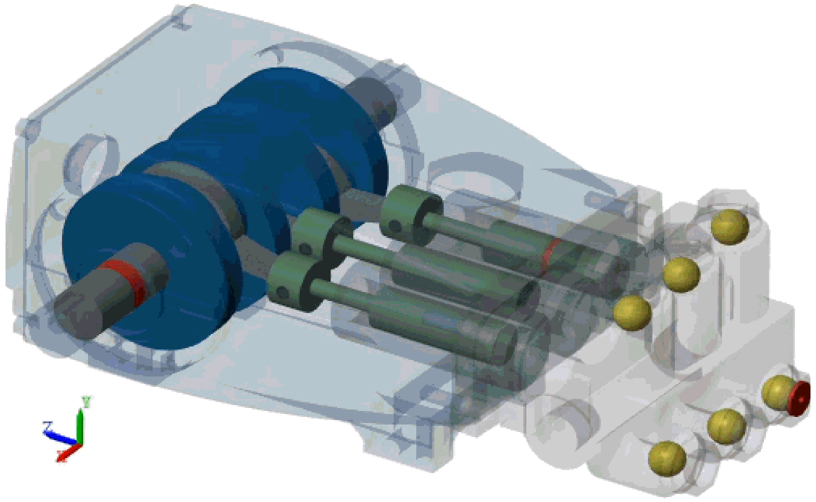



# Reciprocating Pump Example

- Monitor pump condition and predict future condition
- Measure
  - Flow rate
  - Pressure
  - Engine current
- Faults
  - Leaks
  - Worn bearings
  - Blockages



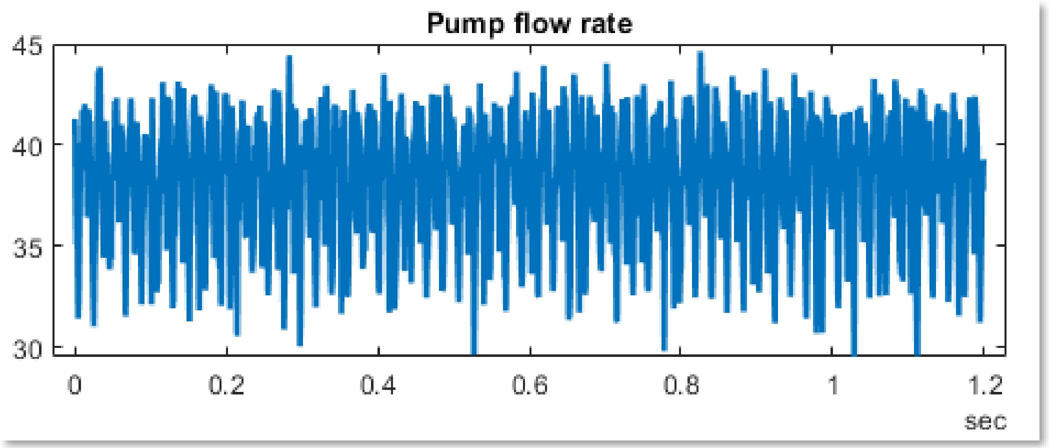
| COMMON SPECIFICATIONS | U.S. | Metric |
|---|---|---|
| Bore | 0.945" | 24 mm |
| Stroke | 1.18" | 30 mm |
| Crankcase Capacity | 42 oz. | 1.26 l |
| Shaft Diameter | 1.181" | 30 mm |

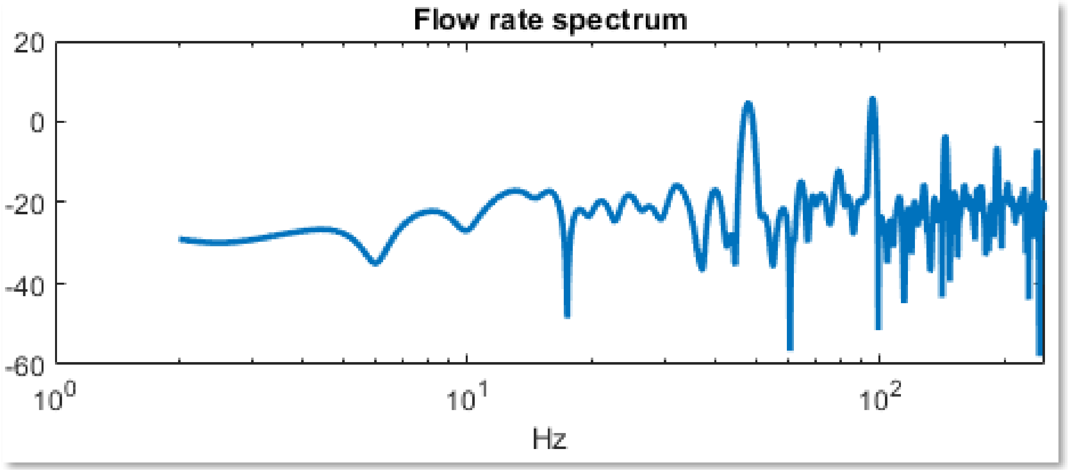


# Frequency Domain Indicators

- Use spectral peaks and harmonics to understand condition of pump

```
% Remove the mean from the flow and compute the flow spectrum
fA = flow;
fA.Data = fA.Data - mean(fA.Data);
[flowSpectrum,flowFrequencies] = pspectrum(fA,'FrequencyLimits',[2 250]);
```



# Classify Faults Based on Condition Indicators

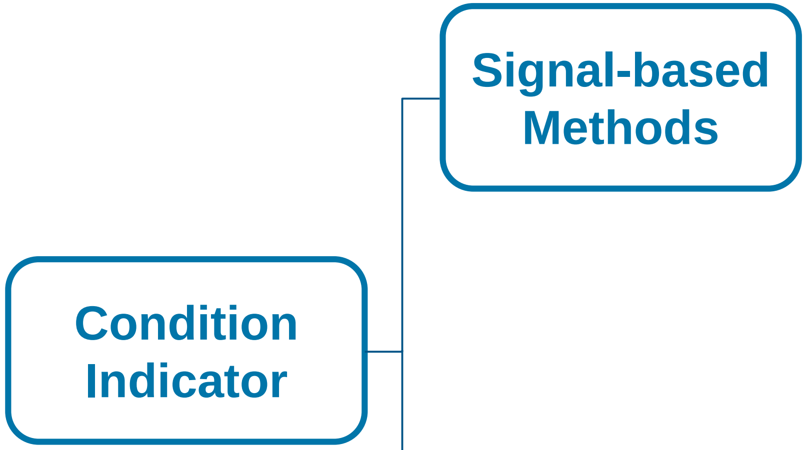
- Train and test a support vector machine

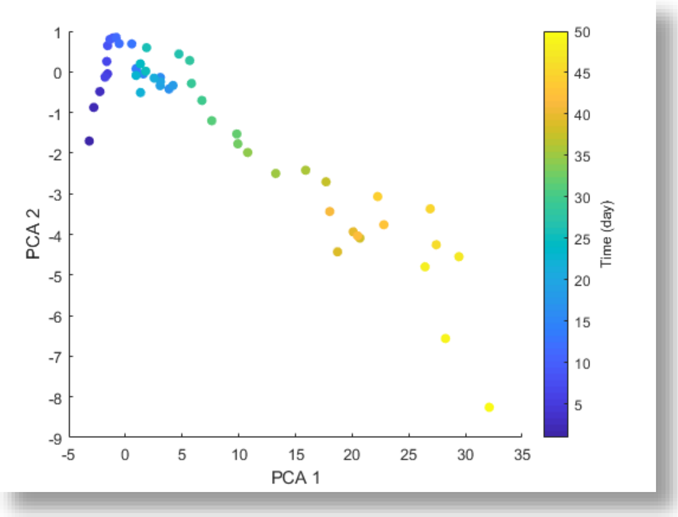
```
% Create and train the classifier
template = templateSVM(...
    'KernelFunction', 'polynomial', ...
    'PolynomialOrder', 2, ...
    'KernelScale', 'auto', ...
    'BoxConstraint', 1, ...
    'Standardize', true);
combinedClassifier = fitcecoc(...
    predictors(cvp.training(1),:), ...
    response(cvp.training(1),:), ...
    'Learners', template, ...
    'Coding', 'onevsone', ...
    'ClassNames', [0; 1; 2; 3; 4; 5; 6; 7]);
```

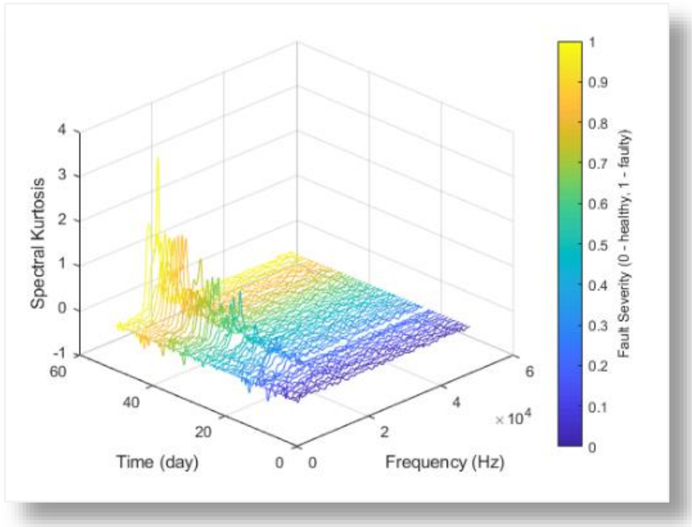
| Actual leak fault | None | Leak | Blocking | Leak & Blocking | Bearing | Bearing & Leak | Bearing & Blocking | All |
|---|---|---|---|---|---|---|---|---|
| None | 35 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Leak | 0 | 24 | 0 | 5 | 0 | 1 | 0 | 0 |
| Blocking | 2 | 0 | 32 | 0 | 0 | 0 | 1 | 0 |
| Leak & Blocking | 0 | 1 | 0 | 14 | 0 | 0 | 0 | 0 |
| Bearing | 2 | 0 | 0 | 0 | 26 | 1 | 2 | 0 |
| Bearing & Leak | 0 | 1 | 0 | 2 | 0 | 10 | 0 | 1 |
| Bearing & Blocking | 0 | 0 | 2 | 1 | 3 | 0 | 15 | 0 |
| All | 0 | 0 | 0 | 0 | 0 | 4 | 1 | 13 |

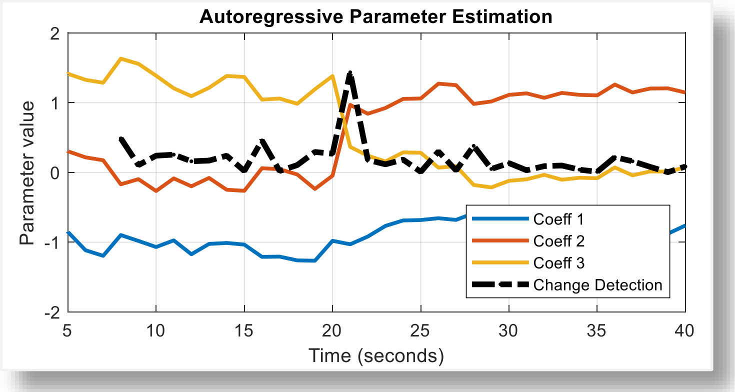
# Other Condition Indicators

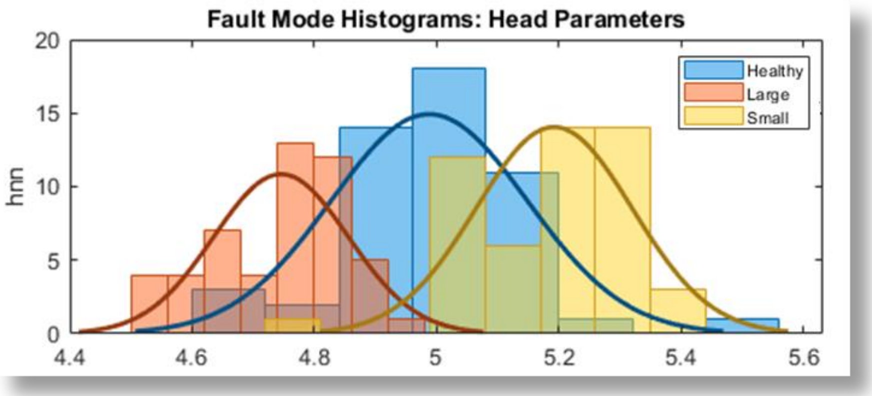
**Extract features using signal-based and model-based methods to determine machine health**



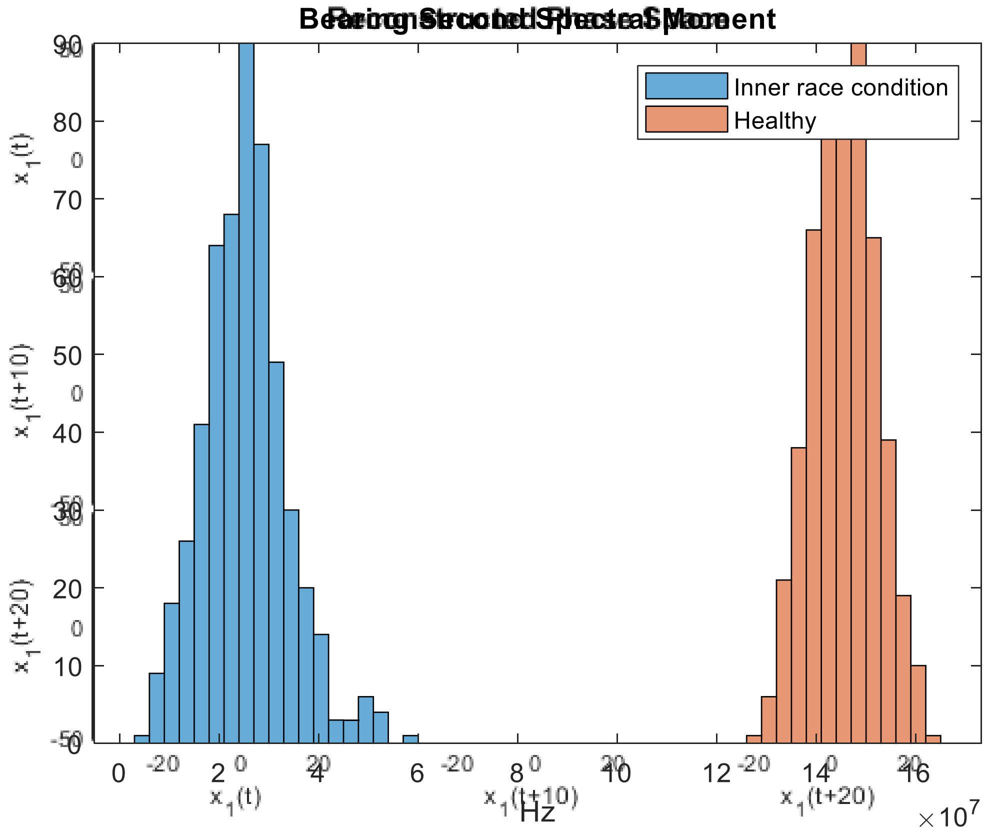



# Advanced Condition Indicators

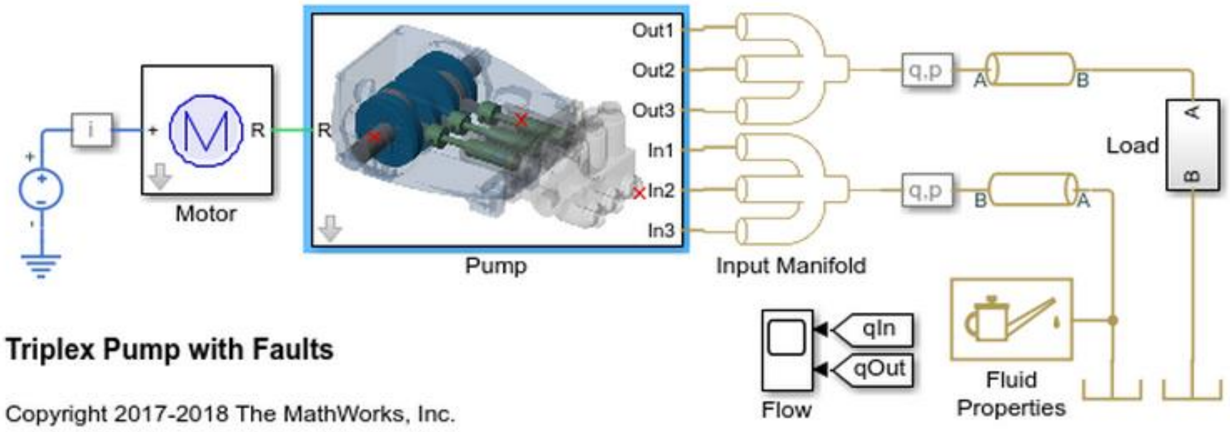
- Capture time-varying dynamics (e.g. vibration data) by computing time-frequency moments

- Detect sudden changes in nonlinear systems using phase-space reconstruction methods (correlation dimension, approximate entropy, Lyapunov exponent)



# Tools for Managing and Analyzing Data

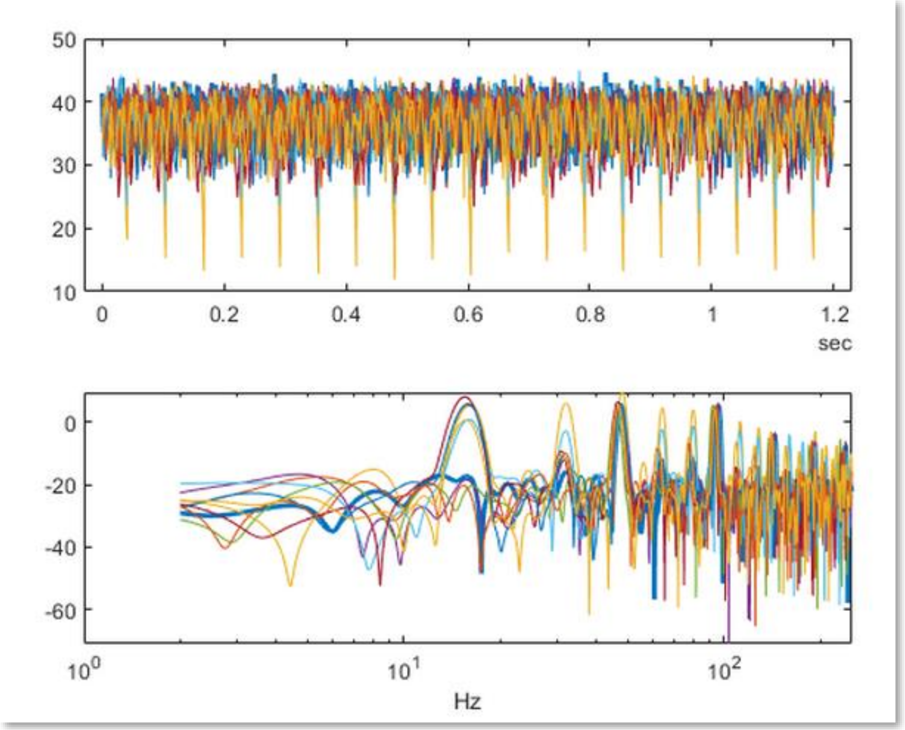
- Generate data using Simulink
- Analyze data using datastores




```
ens = simulationEnsembleDatastore('.\Data');
ens.SelectedVariables = ["qOut_meas", ...
    "pMid", "qVar", "qSkewness", "qKurtosis",...
    "LeakFault", "BlockingFault", "BearingFault"];
dataTable = tall(ens)
```

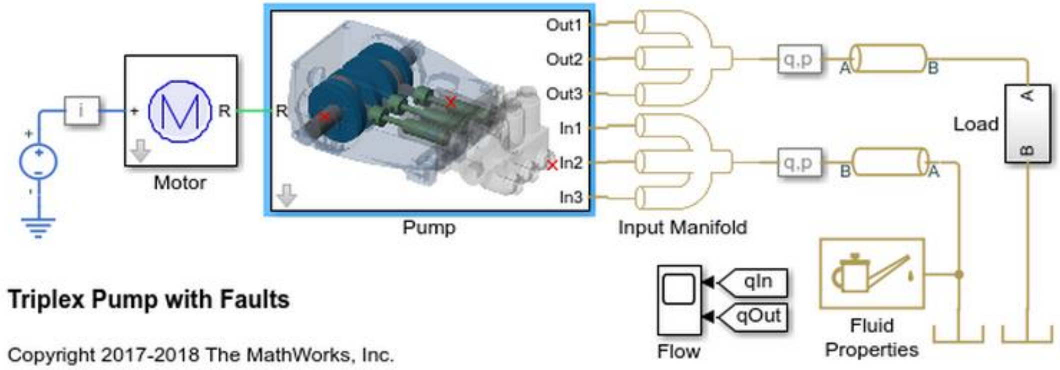
```
dataTable =

  M×8 tall table
```

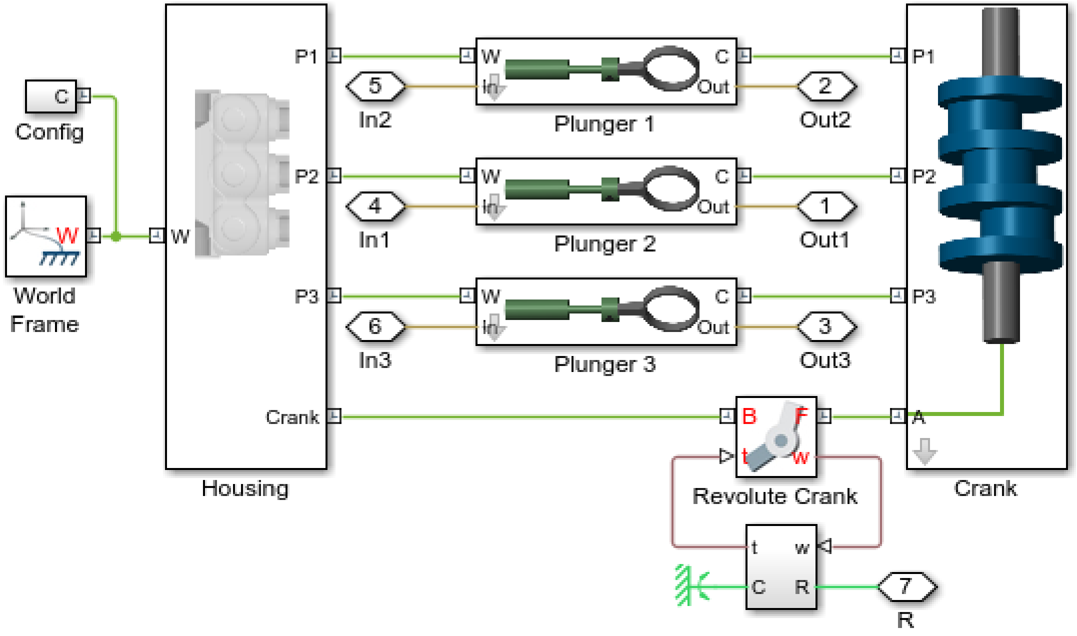
| qOut_meas | pMid | qVar | qSkewness | qKurtosis | LeakFault | BlockingFault | BearingFault |
|---|---|---|---|---|---|---|---|
| [2001×1 timetable] | 103.56 | 9.5309 | -0.55515 | 2.4113 | 1e-09 | 0.8 | 0 |
| [2001×1 timetable] | 87.039 | 9.2684 | -0.57675 | 2.4018 | 1e-09 | 0.8 | 0 |
| [2001×1 timetable] | 117.22 | 9.3804 | -0.54379 | 2.3226 | 1e-09 | 0.8 | 0 |
| [2001×1 timetable] | 97.658 | 9.5407 | -0.5538 | 2.4124 | 4e-07 | 0.74 | 0.0002 |
| [2001×1 timetable] | 106.05 | 9.232 | -0.56334 | 2.4103 | 1e-09 | 0.8 | 0 |
| [2001×1 timetable] | 109.96 | 9.732 | -0.53987 | 2.3798 | 1e-09 | 0.8 | 0 |
| [2001×1 timetable] | 105.06 | 9.4902 | -0.56641 | 2.3461 | 1e-09 | 0.8 | 0 |
| [2001×1 timetable] | 105.1 | 9.2956 | -0.56135 | 2.3623 | 1e-09 | 0.8 | 0 |
| : | : | : | : | : | : | : | : |
| : | : | : | : | : | : | : | : |

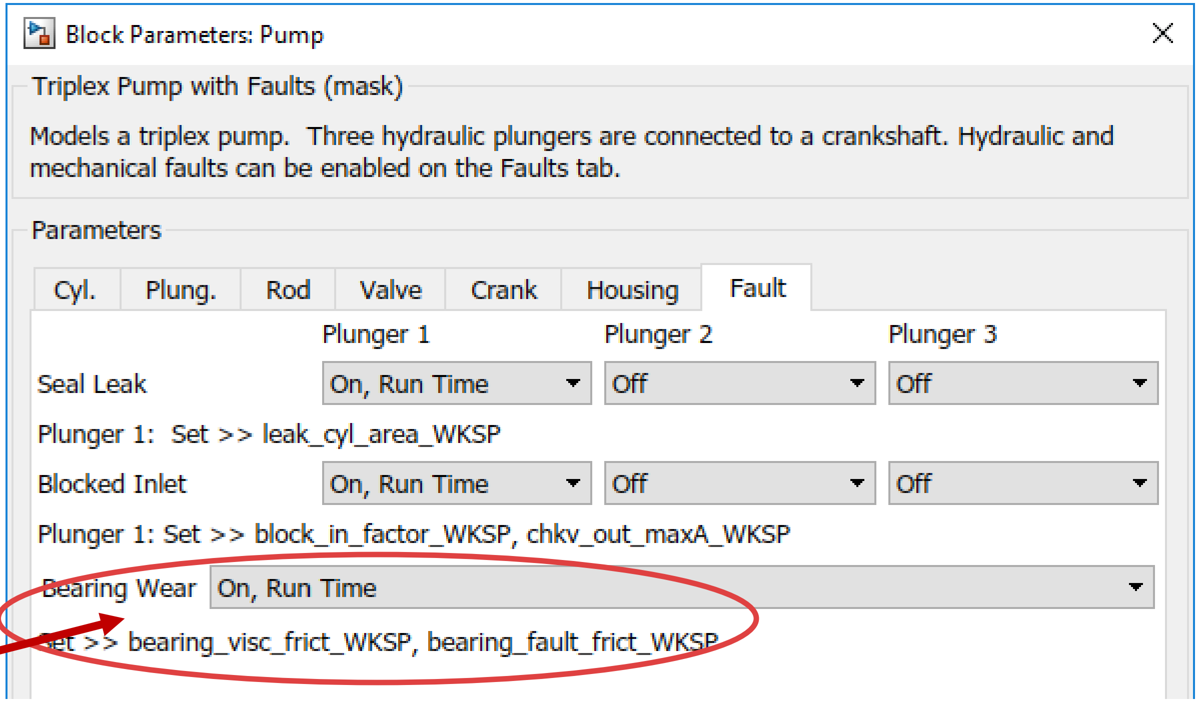


# Modeling Faults In Simulink

- Parameterize Blocks




**FEMA analysis to choose parameters and failure modes**

# Datastore to Manage Data

M×9 tall table

| Date | qOut_meas | pMid | qVar | qSkewness | qKurtosis | LeakFault | BlockingFault | BearingFault |
|---|---|---|---|---|---|---|---|---|
| 16-Jan-2015 | [2001×1 timetable] | 103.56 | 9.5309 | -0.55515 | 2.4113 | 1e-09 | 0.8 | 0 |
| 17-Jan-2015 | [2001×1 timetable] | 87.039 | 9.2684 | -0.57675 | 2.4018 | 1e-09 | 0.8 | 0 |
| 18-Jan-2015 | [2001×1 timetable] | 117.22 | 9.3804 | -0.54379 | 2.3226 | 1e-09 | 0.8 | 0 |
| 19-Jan-2015 | [2001×1 timetable] | 97.658 | 9.5407 | -0.5538 | 2.4124 | 4e-07 | 0.74 | 0.0002 |
| 20-Jan-2015 | [2001×1 timetable] | 106.05 | 9.232 | -0.56334 | 2.4103 | 1e-09 | 0.8 | 0 |
| 21-Jan-2015 | [2001×1 timetable] | 109.96 | 9.732 | -0.53987 | 2.3798 | 1e-09 | 0.8 | 0 |
| 22-Jan-2015 | [2001×1 timetable] | 105.06 | 9.4902 | -0.56641 | 2.3461 | 1e-09 | 0.8 | 0 |
| 23-Jan-2015 | [2001×1 timetable] | 105.1 | 9.2956 | -0.56135 | 2.3623 | 1e-09 | 0.8 | 0 |
| : | : | : | : | : | : | : | : | : |
| : | : | : | : | : | : | : | : | : |

- Ensemble (whole table)
- Member (one row)
- Independent variables
- Data variables
  - Source variables
  - Derived variables
- Condition variables

```
ens = simulationEnsembleDatastore('.\Data');
ens.SelectedVariables = [...
    "qOut_meas", "qVar","qSkewness","qKurtosis",...
    "LeakFault",];
data = read(ens)
```

data = 1×5 table

| | qOut_meas | qVar | qSkewness | qKurtosis | LeakFault |
|---|---|---|---|---|---|
| 1 | *2001×1 tim...* | 9.5309 | -0.5551 | 2.4113 | 1.0000e-09 |

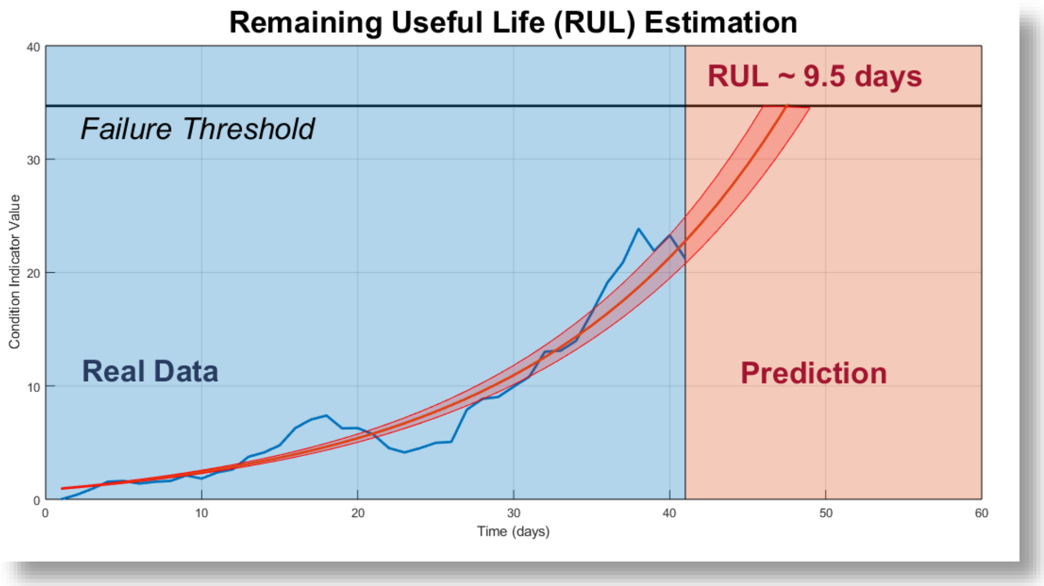
# Sensor And Data Access in MATLAB

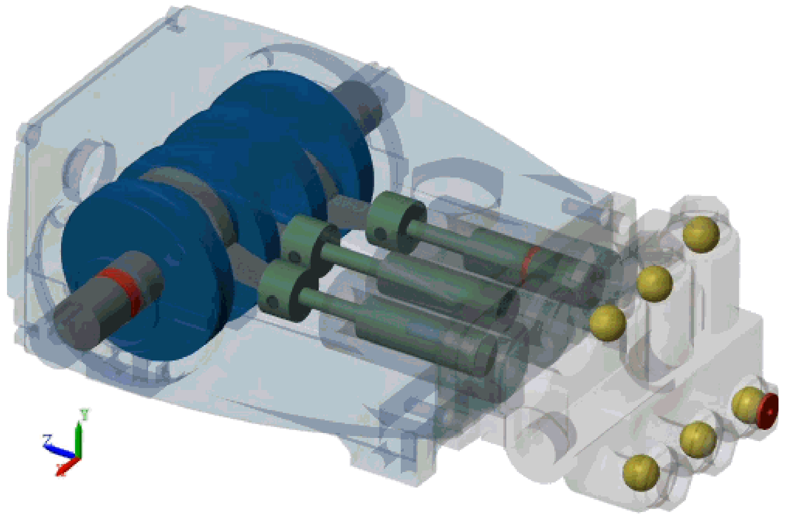
- Data sources accessible through MATLAB
  - Files (.xls, .cvs, .txt, .mat, etc,)
  - Distributed file systems Azure Blob Storage
  - Amazon S3
  - Industrial Internet of Things

.txt

# Predict Pump Failures

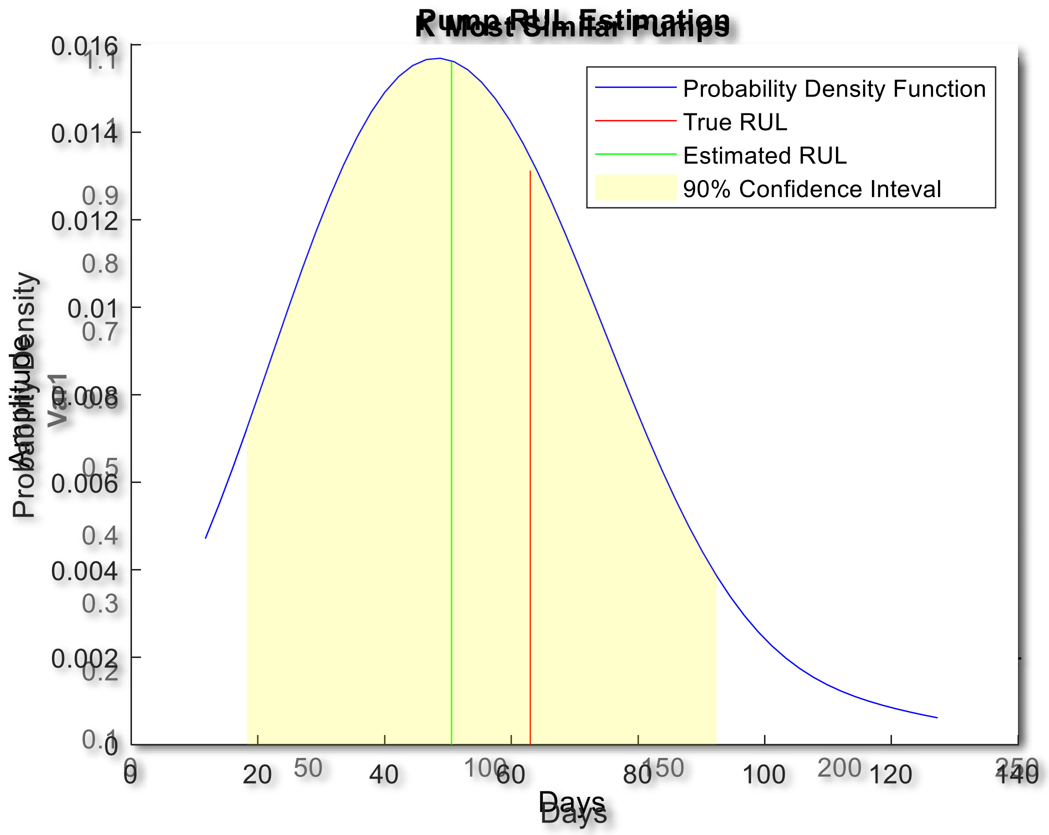
- Use condition indicators to predict future behavior – remaining useful life (RUL)



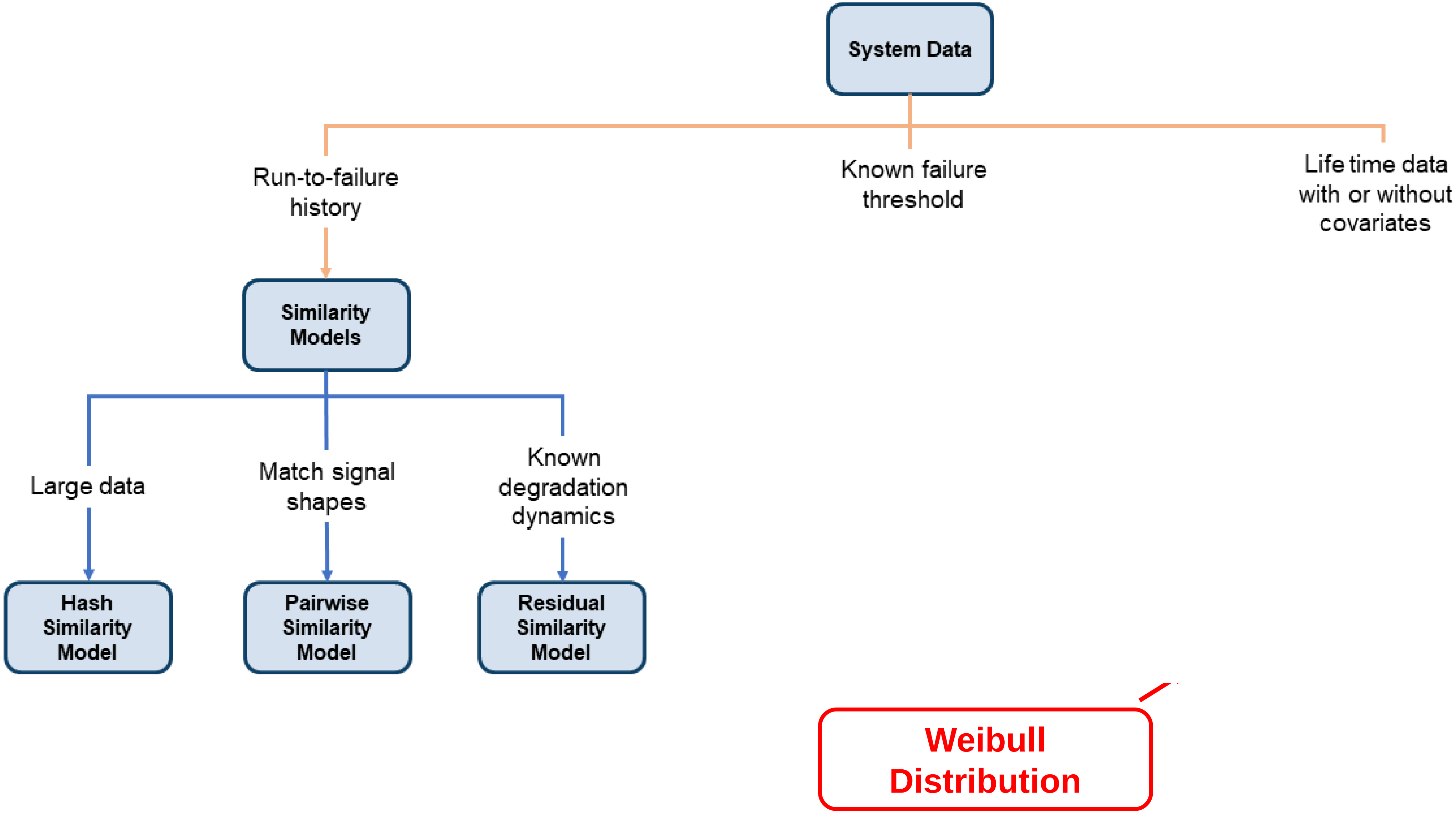
# Using Fleet Data to Predict Remaining Useful Life

```
% Build an train the model
mdl = residualSimilarityModel(...
    'Method', 'poly2',...
    'Distance', 'absolute',...
    'NumNearestNeighbors', 50,...
    'Standardize', 1);
fit(mdl, trainData);

% Use the model to predict RUL
[estRUL,ciRUL,pdfRUL] = predictRUL(mdl, newData);
```



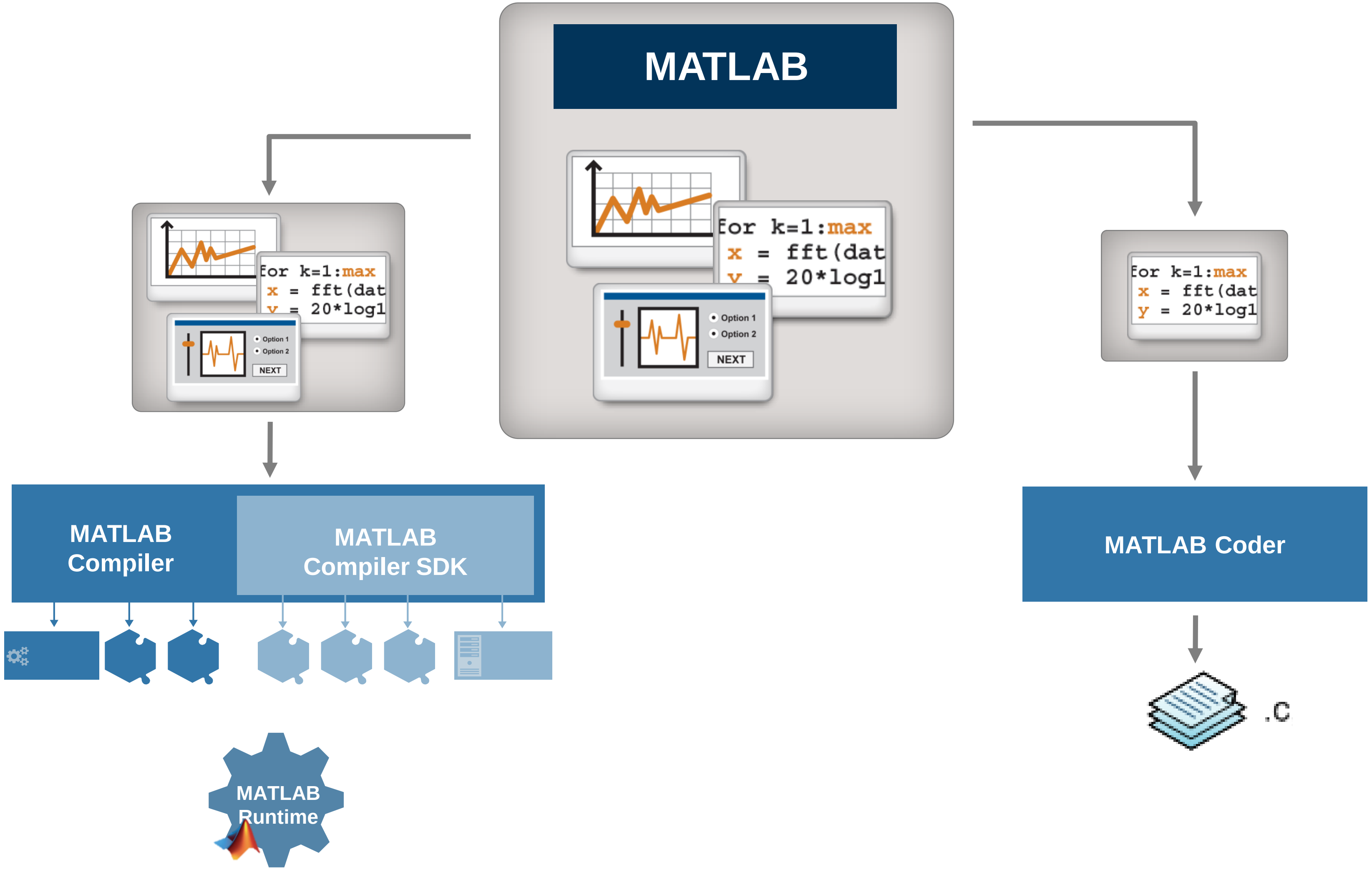
# RUL Methods and when to use them

***Requirement: Need to know what constitutes failure data***



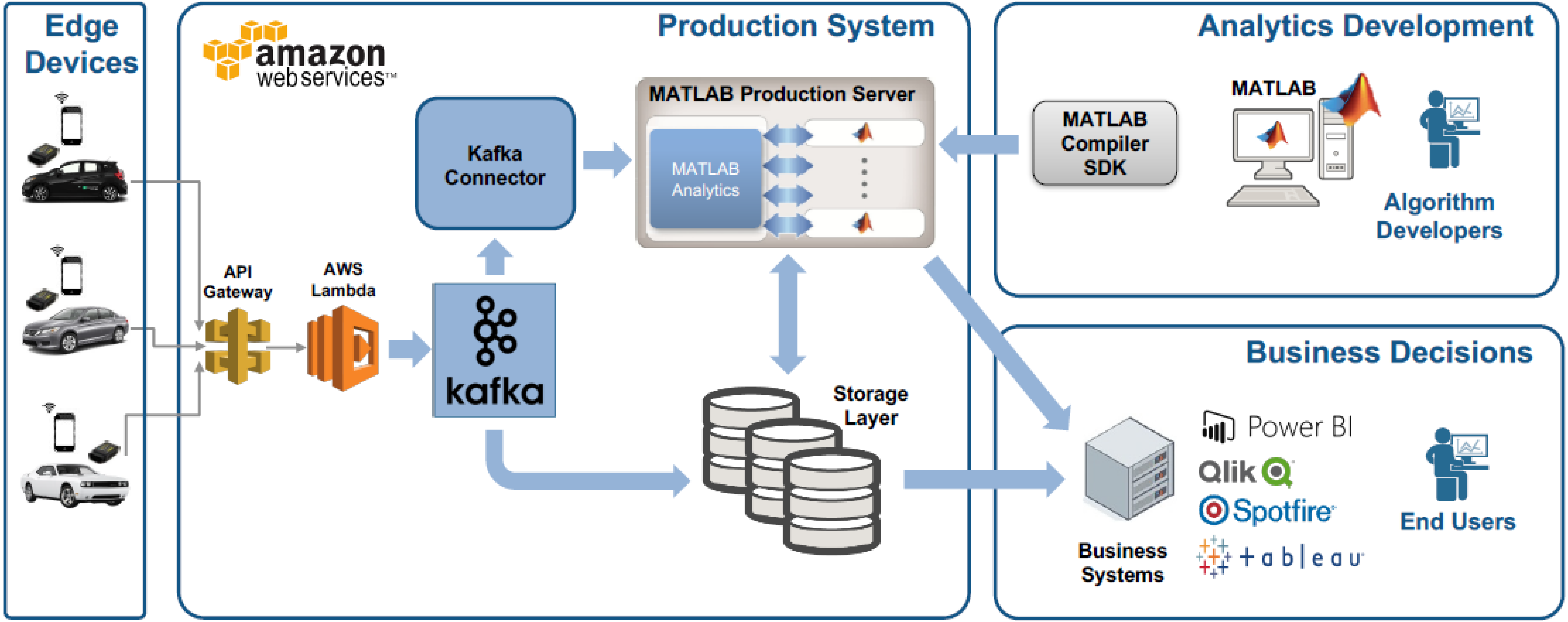
# MATLAB Coder and Compiler

- Run predictive model on embedded devices




# MATLAB Production Server and Enterprise Integration

- Integrate predictive model with your enterprise system and cloud platform

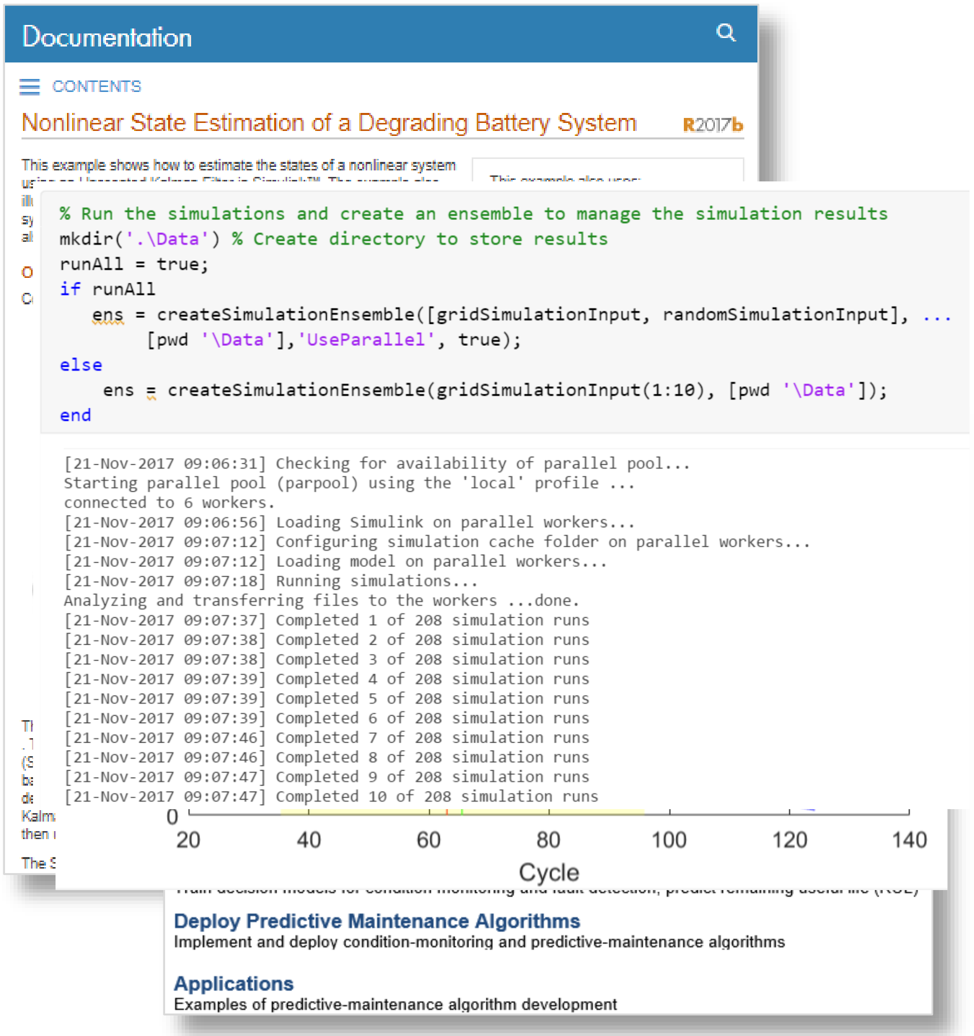


# Predictive Maintenance Development  - Common pains

- How do I get started with developing algorithms?
  - Reference examples
  - Documentation based on the workflow

- How do I manage data and what if I don’t have any data?
  - Command line functions to manage and label data
  - Examples showing Simulink models generating failure data

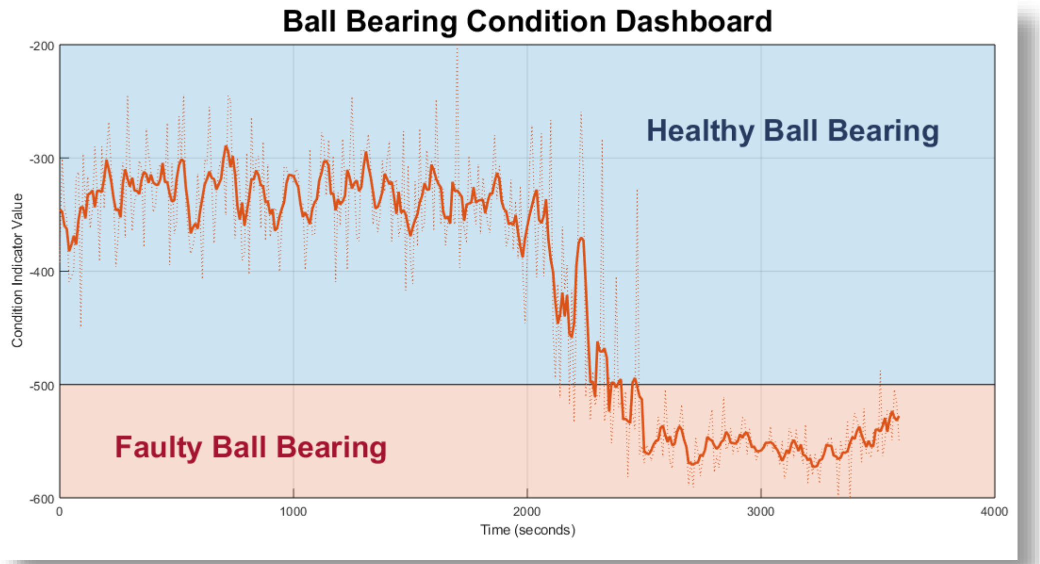
- How do I chose condition indicators and estimate the RUL?
  - Functions provided for estimating RUL
  - Functions for computing condition indicators

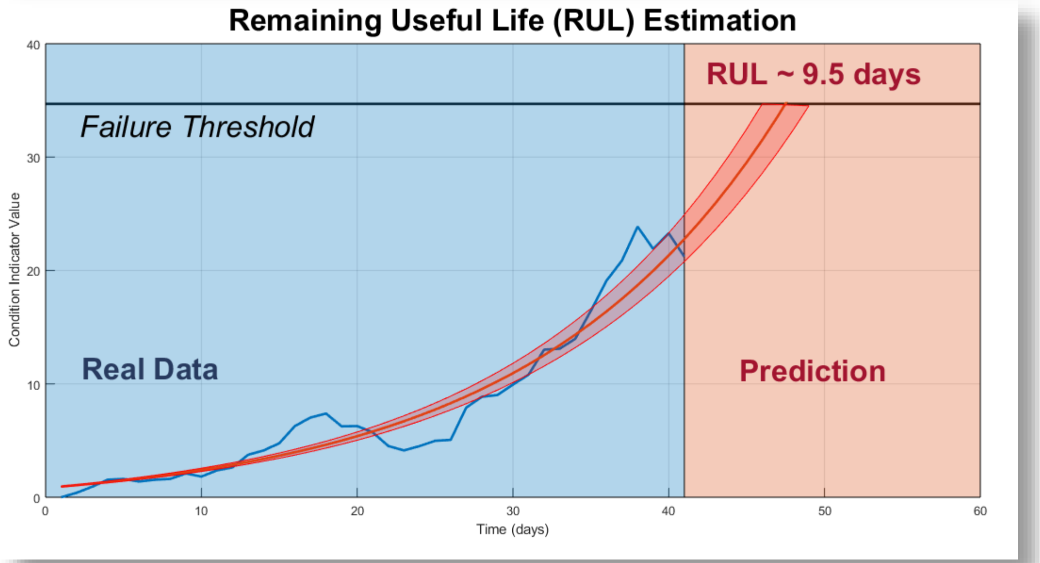


# Predictive Maintenance Toolbox

R2018a

- Develop and validate condition monitoring and predictive maintenance algorithms
- Apply signal processing and dynamic modeling techniques to extract features from your data to monitor machine health
- Train machine learning and time-series models to detect, classify, and predict machine failure
- Use functionality from Signal Processing, Statistics and Machine Learning and System identification



# Thank you!

# Predictive Maintenance Toolbox

R2018a

- Develop and validate condition monitoring and predictive maintenance algorithms
- Apply signal processing and dynamic modeling techniques to extract features from your data to monitor machine health
- Train machine learning and time-series models to detect, classify, and predict machine failure
- Use functionality from Signal Processing, Statistics and Machine Learning and System identification