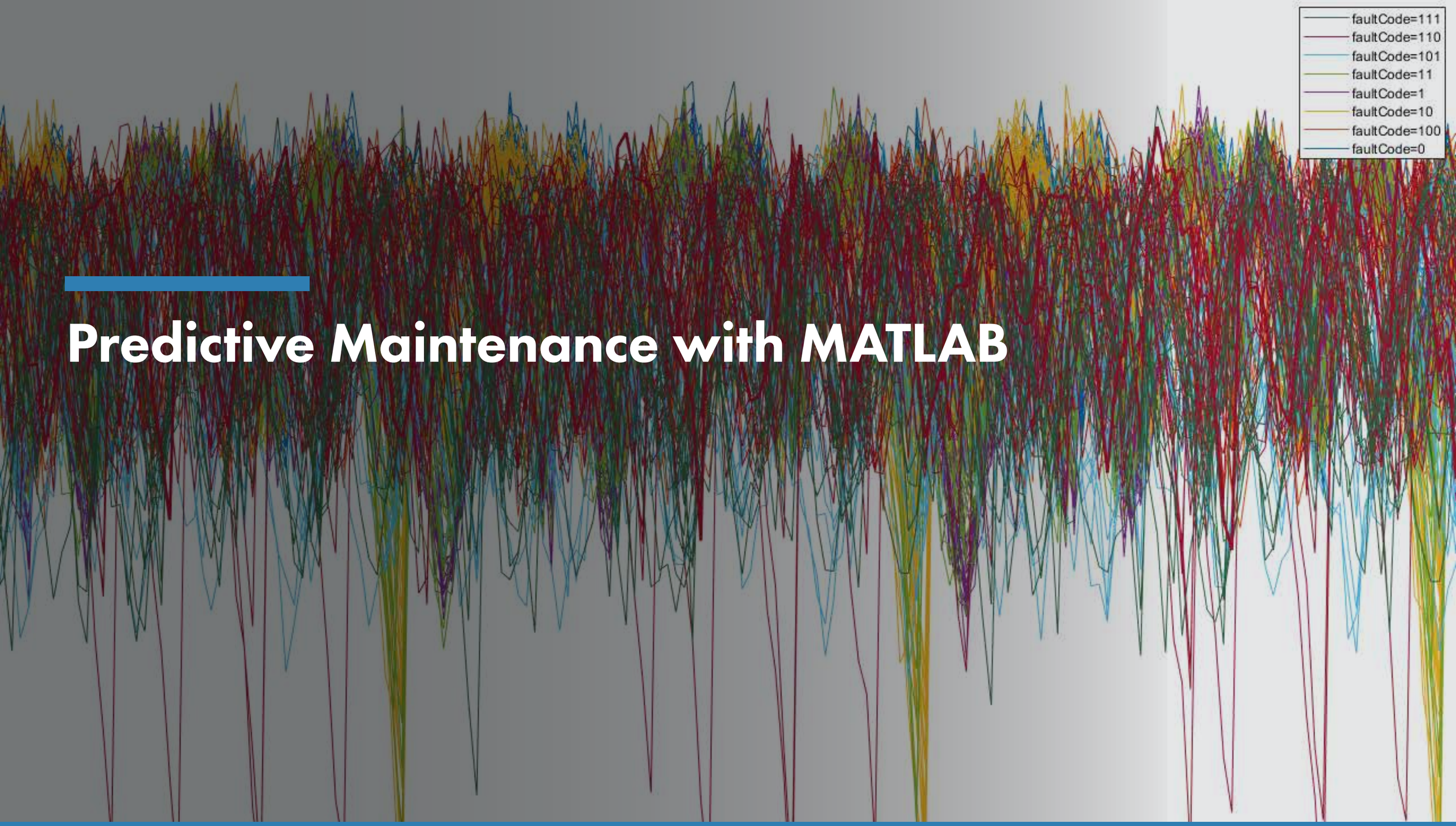

Predictive Maintenance with MATLAB

MathWorks®

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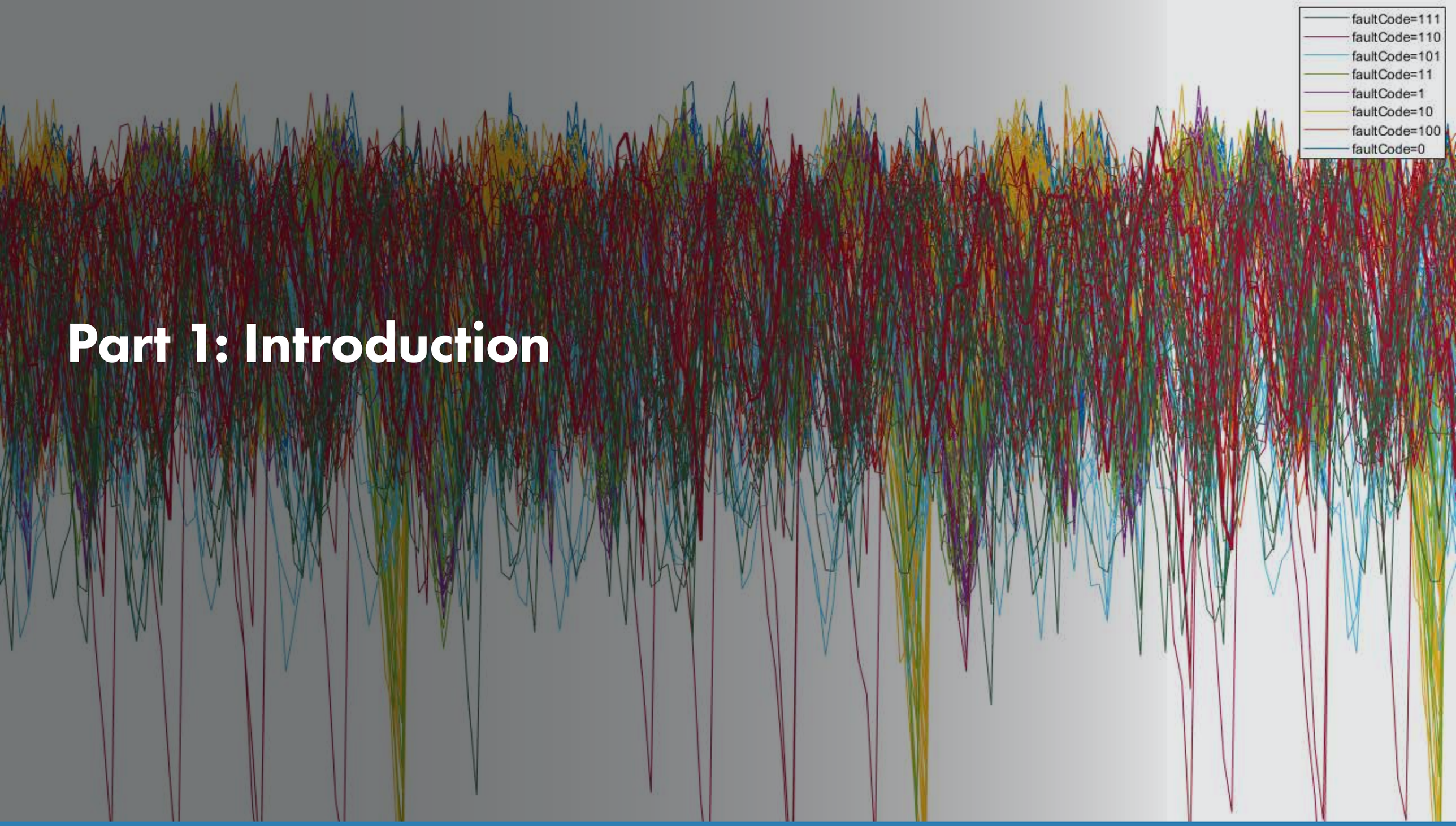
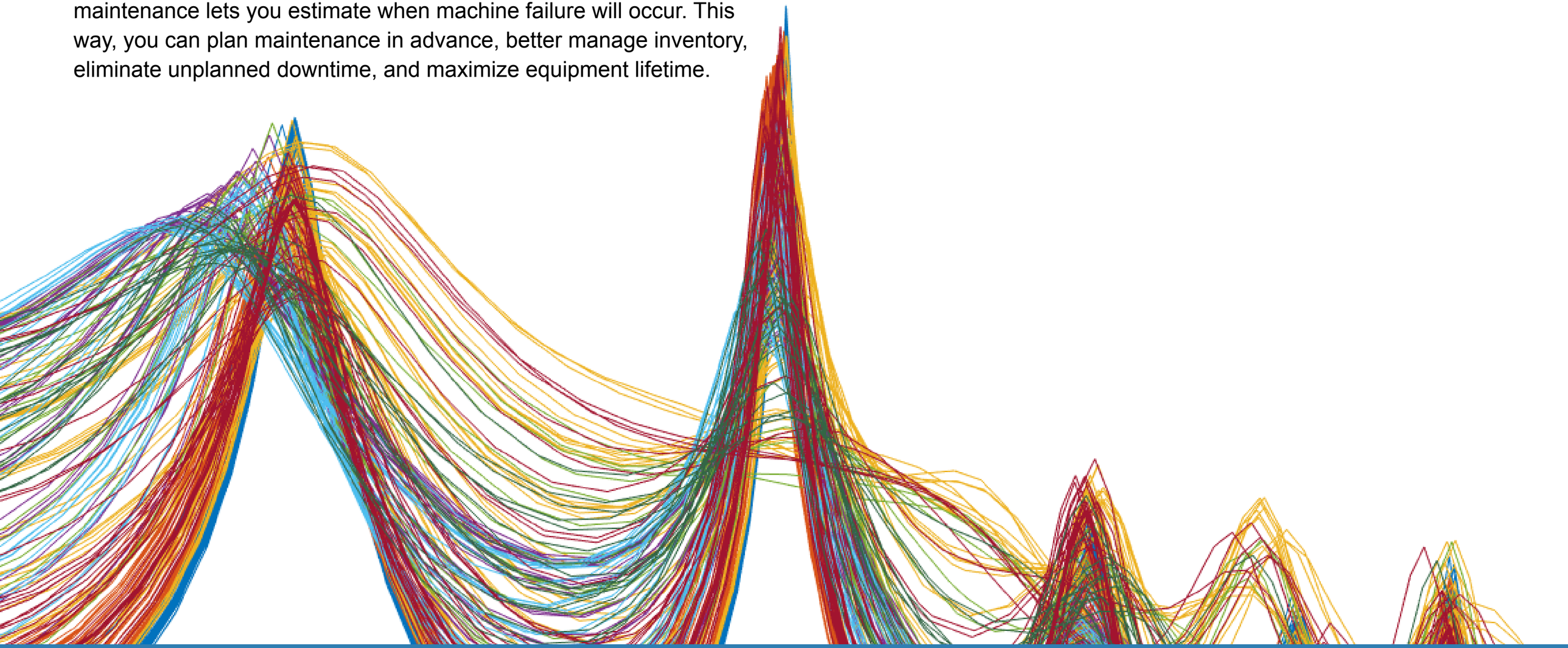


Part 1: Introduction

MathWorks®

What Is Predictive Maintenance?

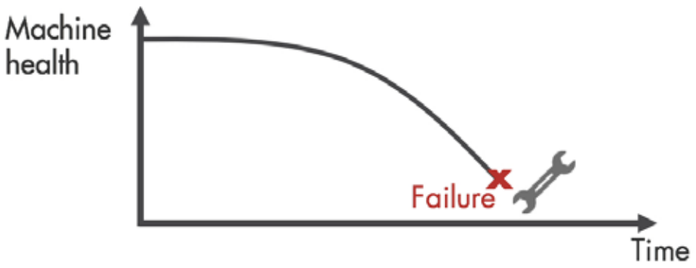
Every day we rely on a wide range of machines, but every machine eventually breaks down unless it’s being maintained. Predictive maintenance lets you estimate when machine failure will occur. This way, you can plan maintenance in advance, better manage inventory, eliminate unplanned downtime, and maximize equipment lifetime.



Maintenance Strategies

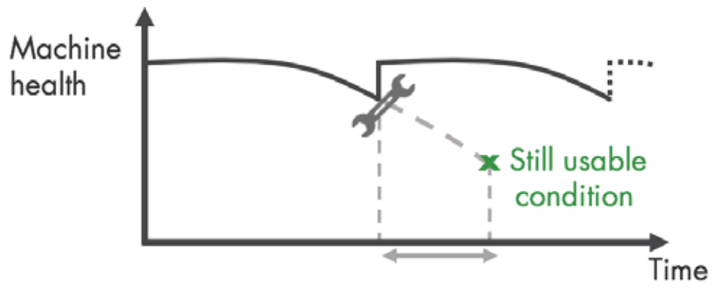
Reactive Maintenance

With reactive maintenance, the machine is used to its limit and repairs are performed only after the machine fails. If you're maintaining an inexpensive system like a light bulb, the reactive approach may make sense. But think of a complex system with some very expensive parts, such as an aircraft engine. You can't risk running it to failure, as it will be extremely costly to repair highly damaged parts. But, more importantly, it's a safety issue.



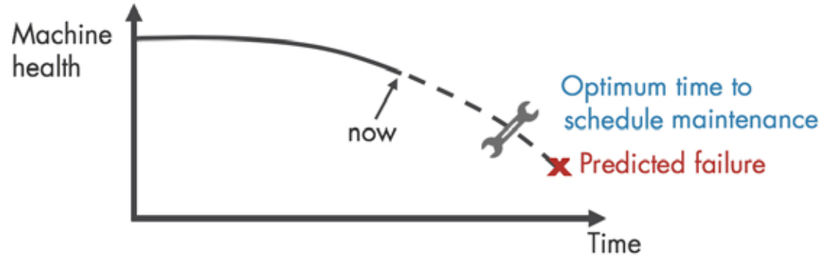
Preventive Maintenance

Many organizations try to prevent failure before it occurs by performing regular checks on their equipment. One big challenge with preventive maintenance is determining when to do maintenance. Since you don't know when failure is likely to occur, you have to be conservative in your planning, especially if you're operating safety-critical equipment. But by scheduling maintenance very early, you're wasting machine life that is still usable, and this adds to your costs.



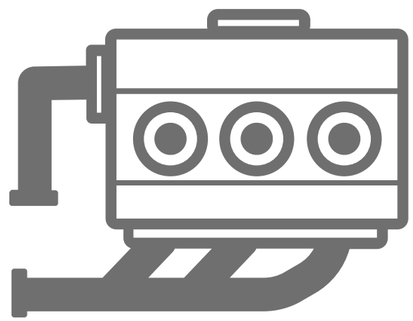
Predictive Maintenance

Predictive maintenance lets you estimate time-to-failure of a machine. Knowing the predicted failure time helps you find the optimum time to schedule maintenance for your equipment. Predictive maintenance not only predicts a future failure, but also pinpoints problems in your complex machinery and helps you identify what parts need to be fixed.



Getting Started with Predictive Maintenance

Implementing predictive maintenance helps reduce downtime, optimize spare parts inventory, and maximize equipment lifetime. But how do you get started? First you need to develop an algorithm that will predict a time window, typically some number of days, when your machine will fail and you need to perform maintenance. Let's look at the predictive maintenance workflow to get started on algorithm development.



Data

Predictive Maintenance Algorithm

Failure in 20±2 days

Predictive Maintenance Workflow at a Glance

Algorithm development starts with **data** that describes your system in a range of healthy and faulty conditions. The raw data is **preprocessed** to bring it to a form from which you can extract **condition indicators.** These are features that help distinguish healthy conditions from faulty. You can then use the extracted features to **train a machine learning model** that can:

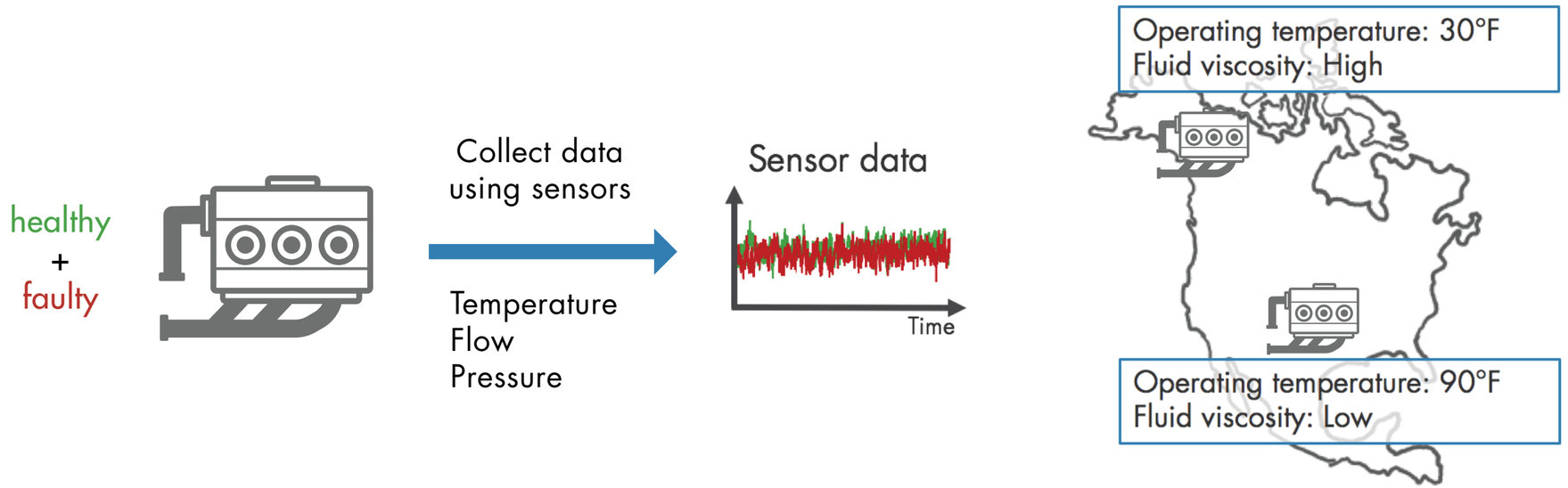
- Detect anomalies
- Classify different types of faults
- Estimate the remaining useful life (RUL) of your machine

Finally, you **deploy** the algorithm and **integrate** it into your systems for machine monitoring and maintenance.

In the next sections, we use a triplex pump example to walk through the workflow steps. Triplex pumps are commonly used in the oil and gas industry.

Acquire Data

The first step is to **collect a large set of sensor data** representing **healthy** and **faulty operation.** It's important to collect this data under varying operating conditions. For example, you may have same type of pumps running in different places, one in Alaska and the other one in Texas. One may be pumping highly viscous fluid whereas the other one operates with low-viscosity fluid. Although you have the same type of pump, one may fail sooner than the other due to these different **operating conditions.** Capturing all this data will help you develop a **robust algorithm** that can better detect faults.

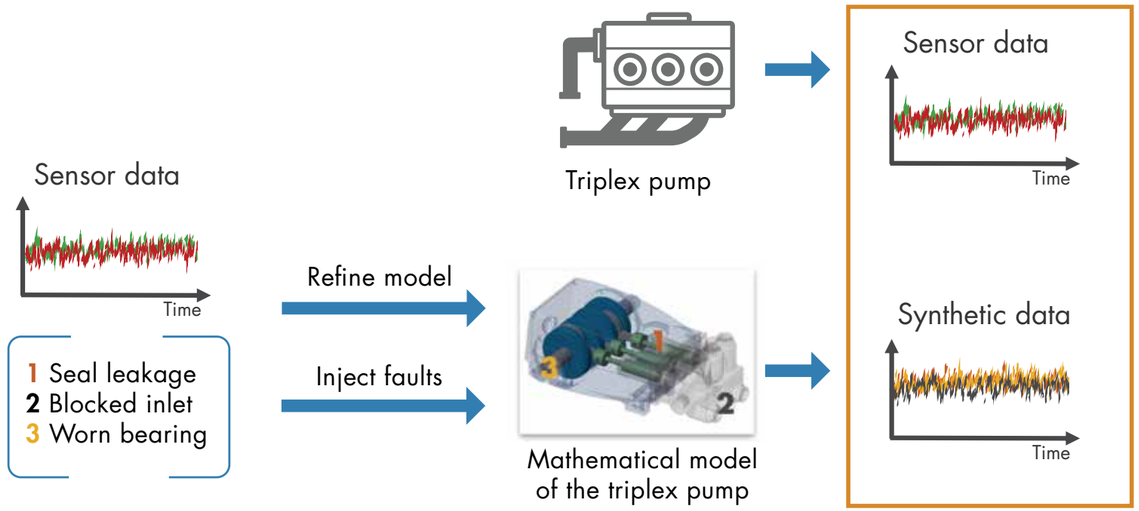


Note: For simplicity in this example, healthy and faulty operations are each represented by a single measurement. In a real-world scenario, there may be hundreds of measurements for both types of conditions.

Acquire Data - Continued

In some cases, you may not have enough data representing healthy and faulty operation. As an alternative, you can build a **mathematical model of the pump** and estimate its parameters from sensor data. You can then simulate this model with different fault states under varying operating conditions to **generate fault data.** This data, also referred to as **synthetic data**, now supplements your sensor data. You can use a combination of synthetic and sensor data to develop your predictive maintenance algorithm.

Learn more: *Generate fault data with Simulink*



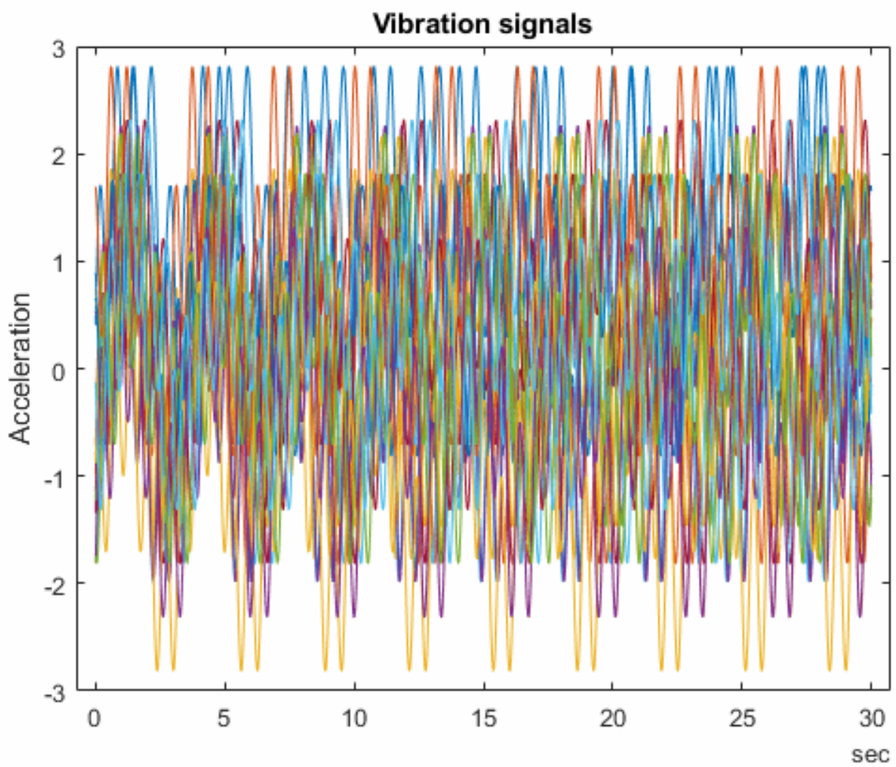
Simulating the model under different fault states to generate fault data.

Acquire Data with MATLAB

Data from equipment can be structured or unstructured, and reside in multiple sources such as local files, the cloud (e.g., AWS® S3, Azure® Blob), databases, and data historians. Wherever your data is, you can get to it with MATLAB®. When you don't have enough failure data, you can generate it from a Simulink® model of your machine equipment by injecting signal faults, and modeling system failure dynamics.

> *MATLAB gave us the ability to convert previously unreadable data into a usable format; automate filtering, spectral analysis, and transform steps for multiple trucks and regions; and ultimately, apply machine learning techniques in real time to predict the ideal time to perform maintenance.*
>
> —Gulshan Singh, Baker Hughes

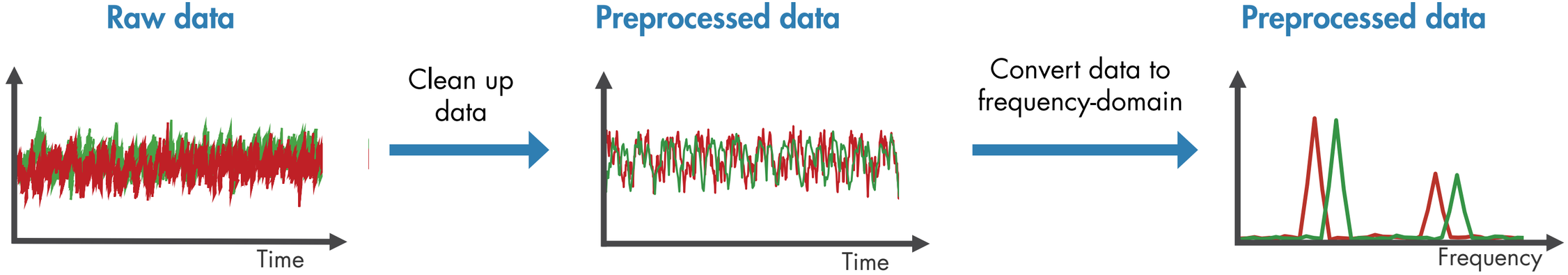
» *Read user story*



Synthetic fault data for a transmission model generated with Simulink.

Preprocess Data

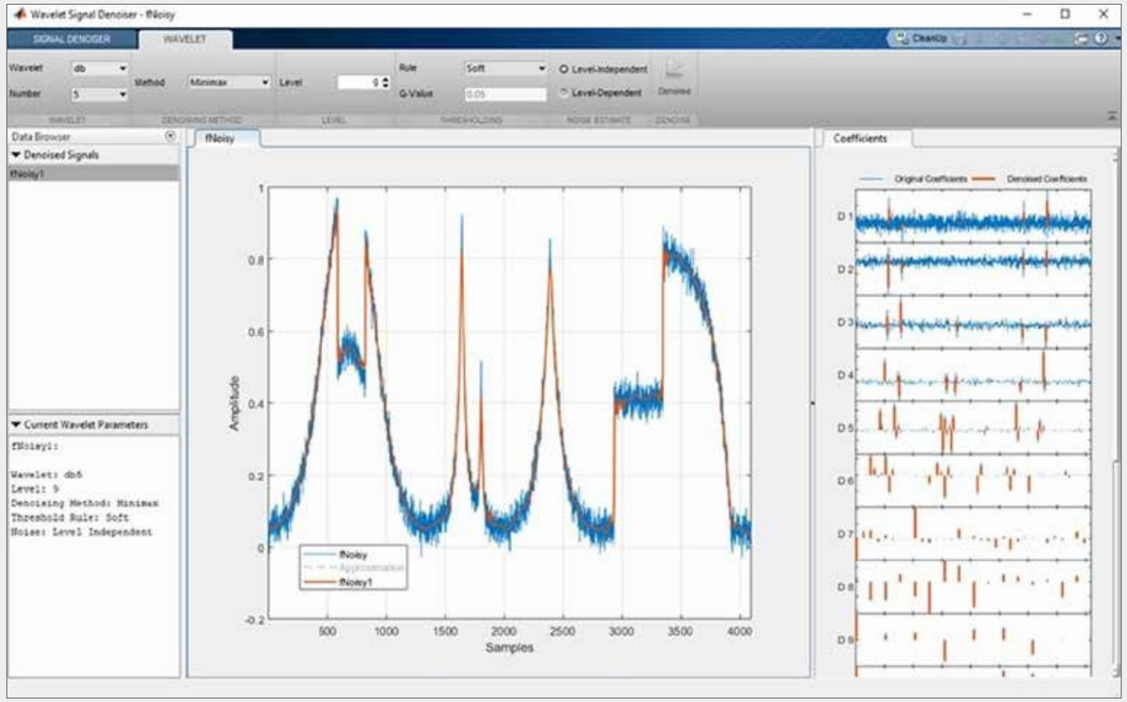
Once you have the data, the next step is to **preprocess the data** to convert it to a form from which condition indicators can be easily extracted. Preprocessing includes techniques such as **noise, outlier,** and **missing value removal.** Sometimes further preprocessing is necessary to reveal additional information that may not be apparent in the original form of the data. For example, this preprocessing may include conversion of time-domain data to **frequency-domain.**



Preprocess Data with MATLAB

Data is messy. With MATLAB, you can preprocess it, reduce its dimensionality, and engineer features:

- Align data that is sampled at different rates, and account for missing values and outliers.
- Remove noise, filter data, and analyze transient or changing signals using advanced signal processing techniques.
- Simplify datasets and reduce overfitting of predictive models using statistical and dynamic methods for feature extraction and selection.

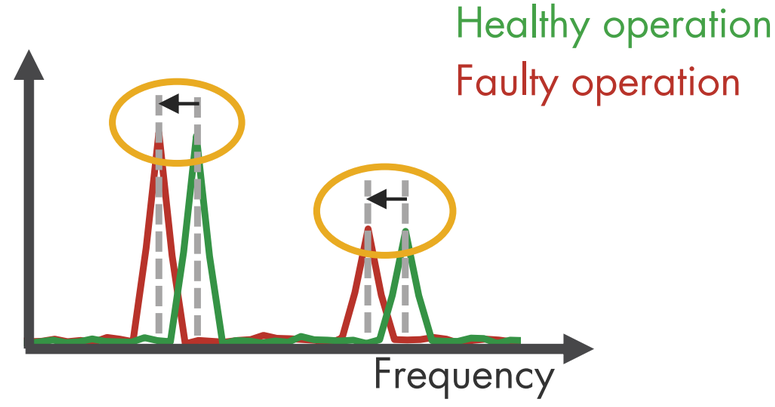


Wavelet Signal Denoiser app for visualizing and denoising signals and comparing results.

Identify Condition Indicators

The next step is to identify **condition indicators,** features whose behavior changes in a predictable way as the system degrades. These features are used to **discriminate between healthy and faulty operation.**

In the plot on the right, the peaks in the frequency data shift left as the pump degrades; therefore, the peak frequencies can serve as condition indicators.

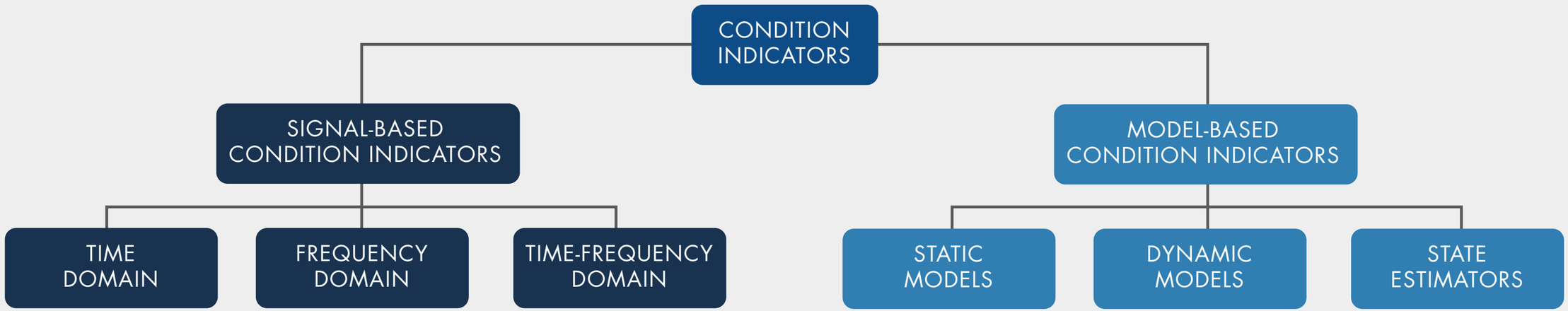


Peak frequencies can serve as **condition indicators.**

Identify Condition Indicators with MATLAB

MATLAB and Predictive Maintenance Toolbox™ let you design condition indicators using both signal-based and model-based approaches. You can calculate time-frequency moments that enable you to capture time-varying dynamics, which are frequently seen when analyzing vibration data. To detect sudden changes in data collected from machines displaying nonlinear behavior or characteristics, you can compute features based on phase-space reconstructions that track changes in your system's state over time.

Learn more: *What Is Predictive Maintenance Toolbox?* (2:00) - Video



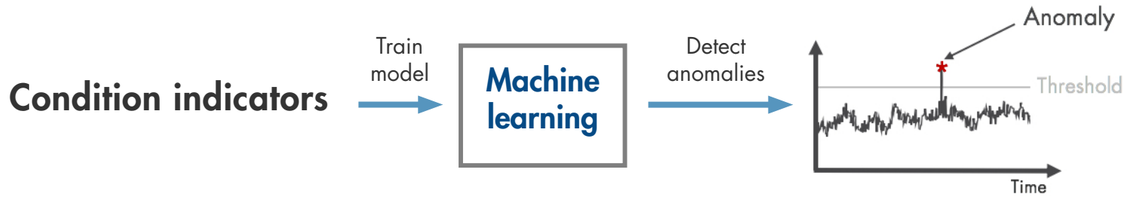
Designing condition indicators using signal-based and model-based methods to monitor the health of your machinery.

Train the Model

So far, you've extracted some features from your data that help you understand healthy and faulty operation of the pump. But at this stage, it's not clear what part needs repair or how much time there is until failure. In the next step, you can use the extracted features to **train machine learning models** to do several things.

Detect anomalies

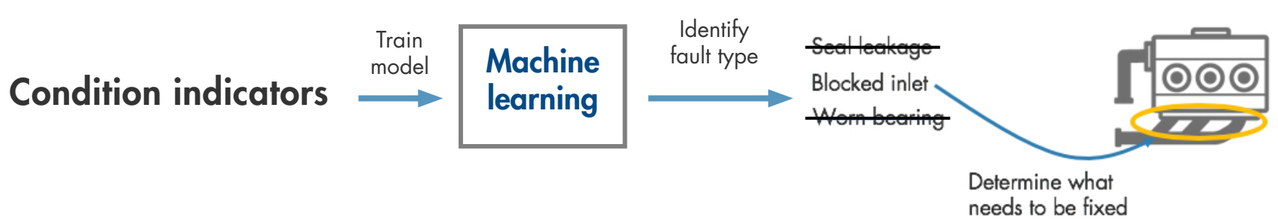
You can track changes in your system to determine the presence of anomalies.



Learn more: *Anomaly Detection for Powertrain Production at Mercedes-Benz*

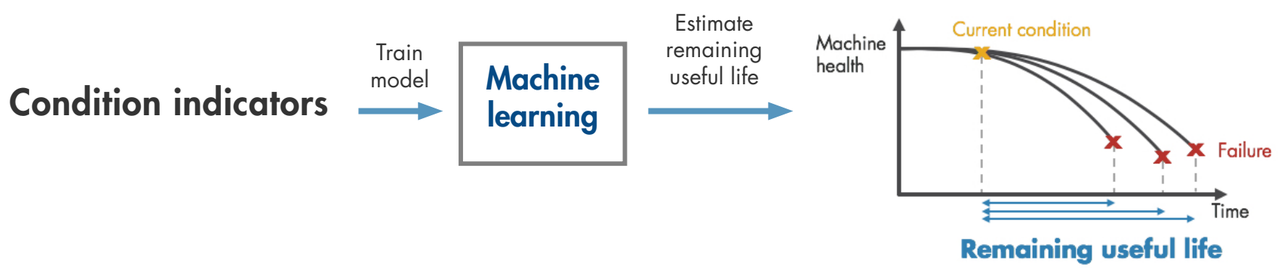
Detect different types of faults through classification

You can gain insight into what part of the pump requires attention.



Predict the transition from healthy state and failure

Finding a model that captures the relationship between the extracted features and the degradation path of the pump will help you estimate how much time there is until failure (**remaining useful life**) and when you should schedule maintenance.

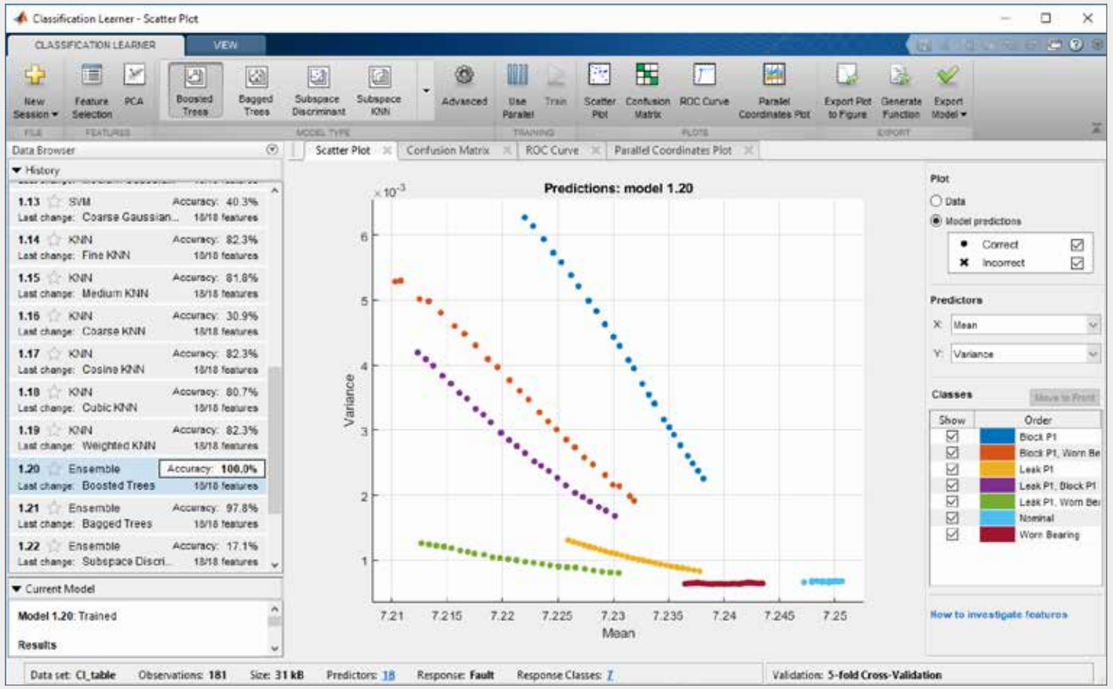


Learn more: *Three Ways to Estimate Remaining Useful Life with MATLAB*

Train the Model Using Machine Learning with MATLAB

You can identify the root cause of failures and predict time-to-failure using classification, regression, and time-series modeling techniques in MATLAB:

- Interactively explore and select the most important variables for estimating RUL or classifying failure modes.
- Train, compare, and validate multiple predictive models with built-in functions.
- Calculate and visualize confidence intervals to quantify uncertainty in predictions.



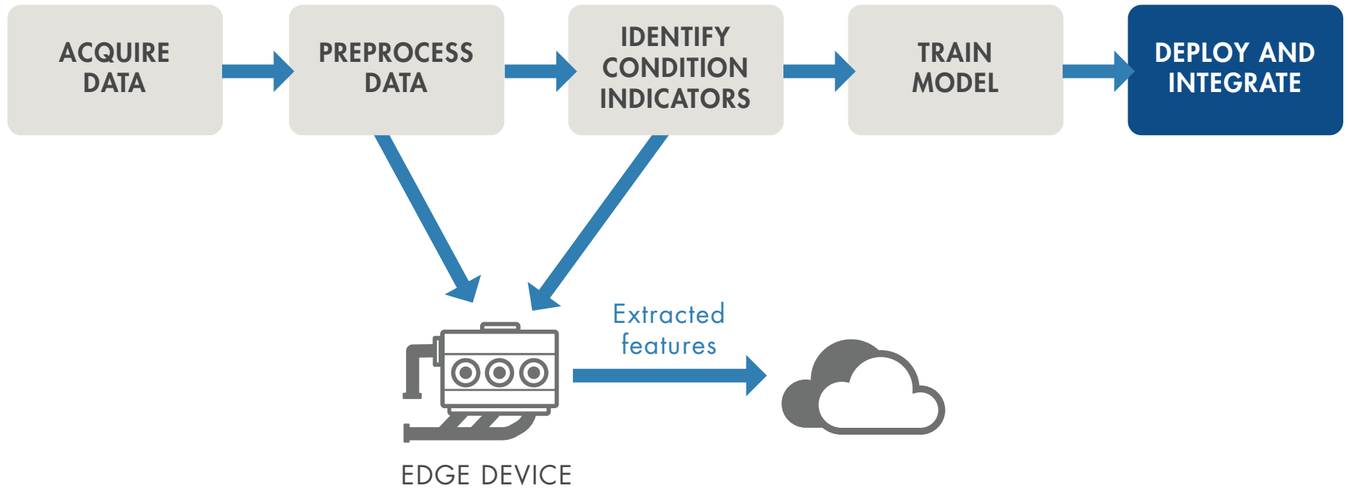
Classification Learner app for trying different classifiers on your dataset. Find the best fit with common models like decision trees and support vector machines.

Deploy and Integrate

After developing your algorithm, you can get it up and running by **deploying** it on the **cloud** or on your **edge device**. A cloud implementation can be useful when you are also gathering and storing large amounts of data on the cloud.

Alternatively, the algorithm can run on embedded devices that are closer to the actual equipment. This may be the case if an internet connection is not available.

A third option is to use a combination of the two. If you have a large amount of data, and if there are limits on how much data you can transmit, you can perform the preprocessing and feature extraction steps on your edge device and then send only the extracted features to your prediction model that runs on the cloud.



Deploy Algorithms in Production Systems with MATLAB

Data scientists often refer to the ability to share and explain results as *model interpretability*. A model that is easily interpretable has:

- A small number of features that typically are created from some physical understanding of the system
- A transparent decision-making process

Interpretability is important for applications when you need to:

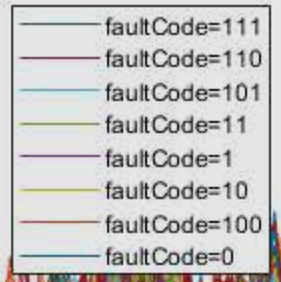
- Prove that your model complies with government or industry standards
- Explain factors that contributed to a diagnosis
- Show the absence of bias in decision-making

> *We operate our machines nonstop, even on Christmas, and we rely on our MATLAB based monitoring and predictive maintenance software to run continuously and reliably in production.*
>
> —Dr. Michael Kohlert, Mondi

» *Read user story*

Share standalone MATLAB applications or run MATLAB analytics as a part of web, database, desktop, and enterprise applications without having to create custom infrastructure.

Learn More



Watch

Predictive Maintenance Tech Talks - Video Series
Predictive Maintenance in MATLAB and Simulink (35:54) - Video

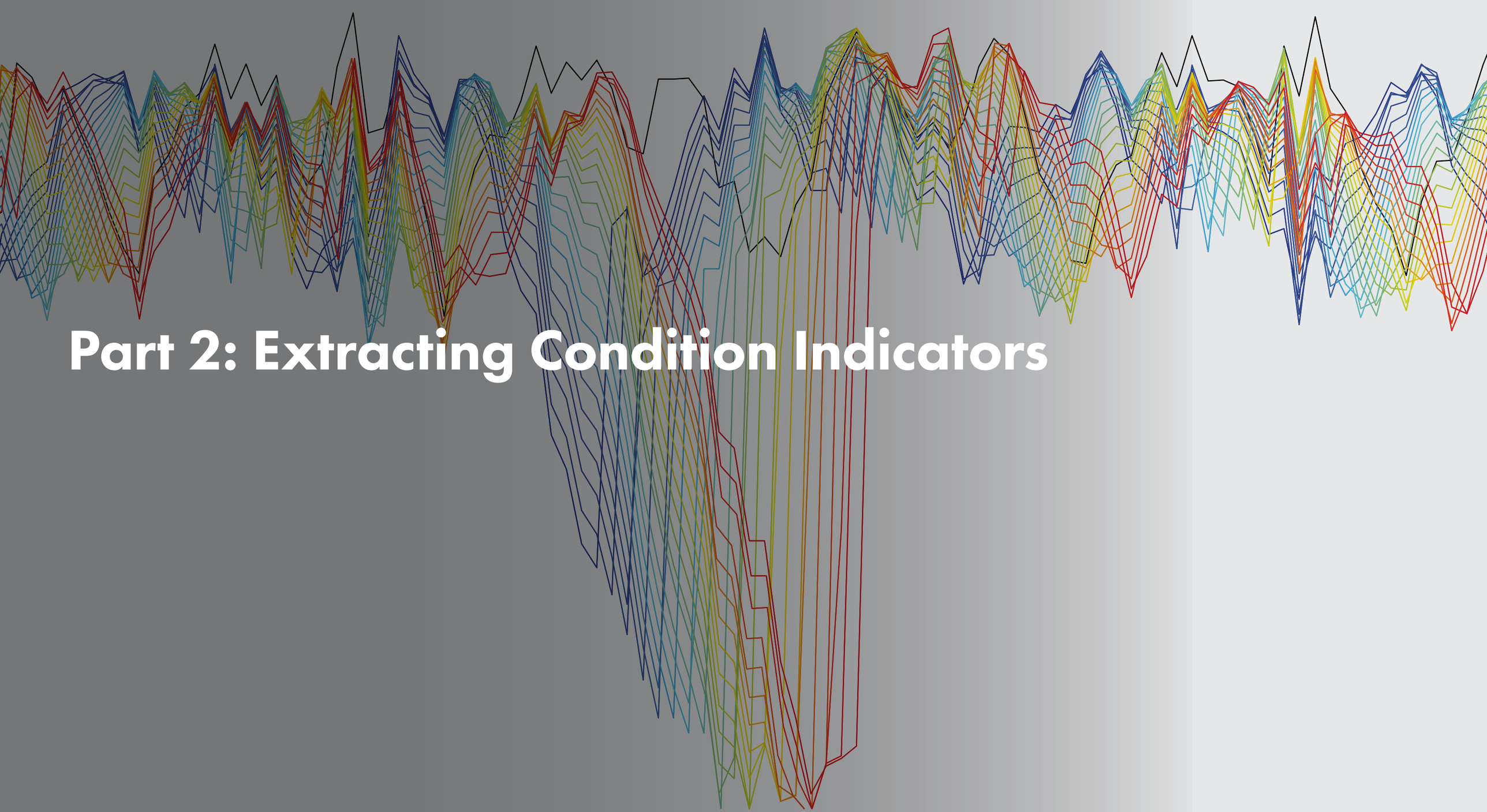
Read

Overcoming Four Common Obstacles to Predictive Maintenance - White Paper

Explore

Predictive Maintenance with MATLAB - Code Examples
Predictive Maintenance Toolbox

Try Predictive Maintenance Toolbox

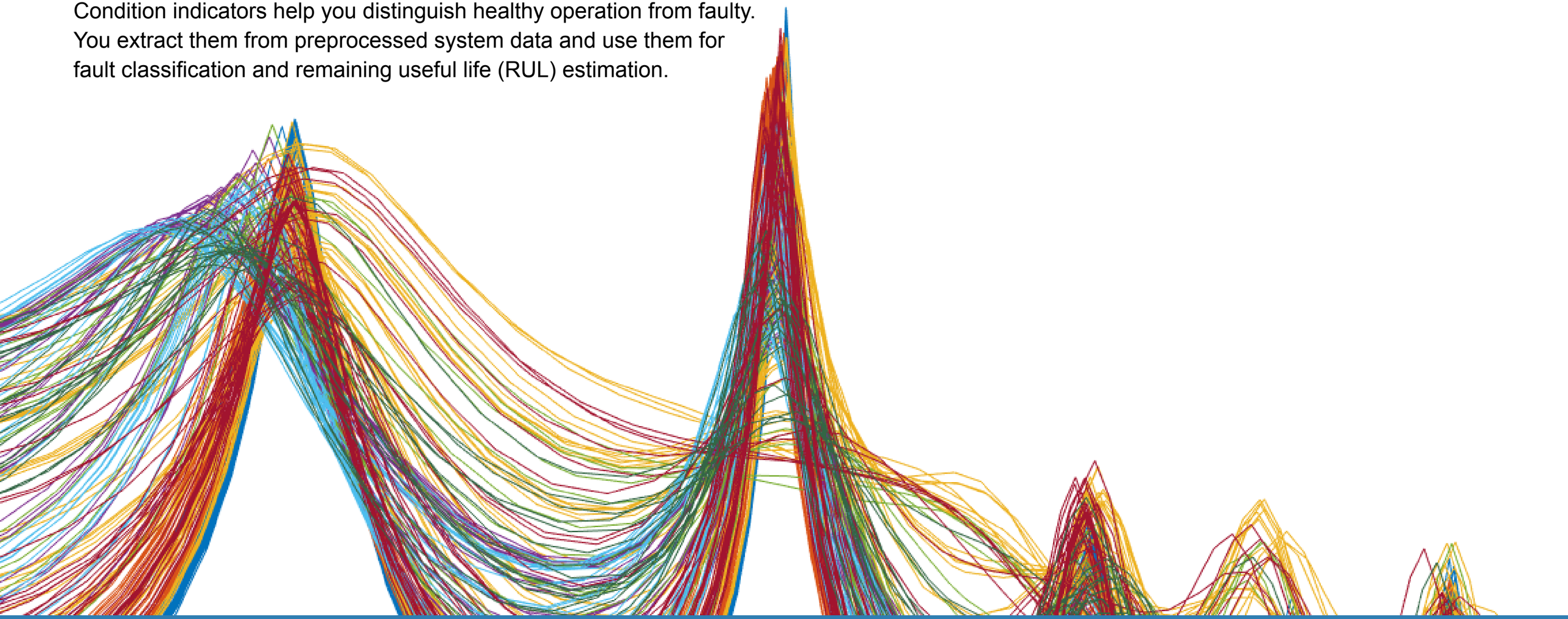


Part 2: Extracting Condition Indicators

MathWorks®

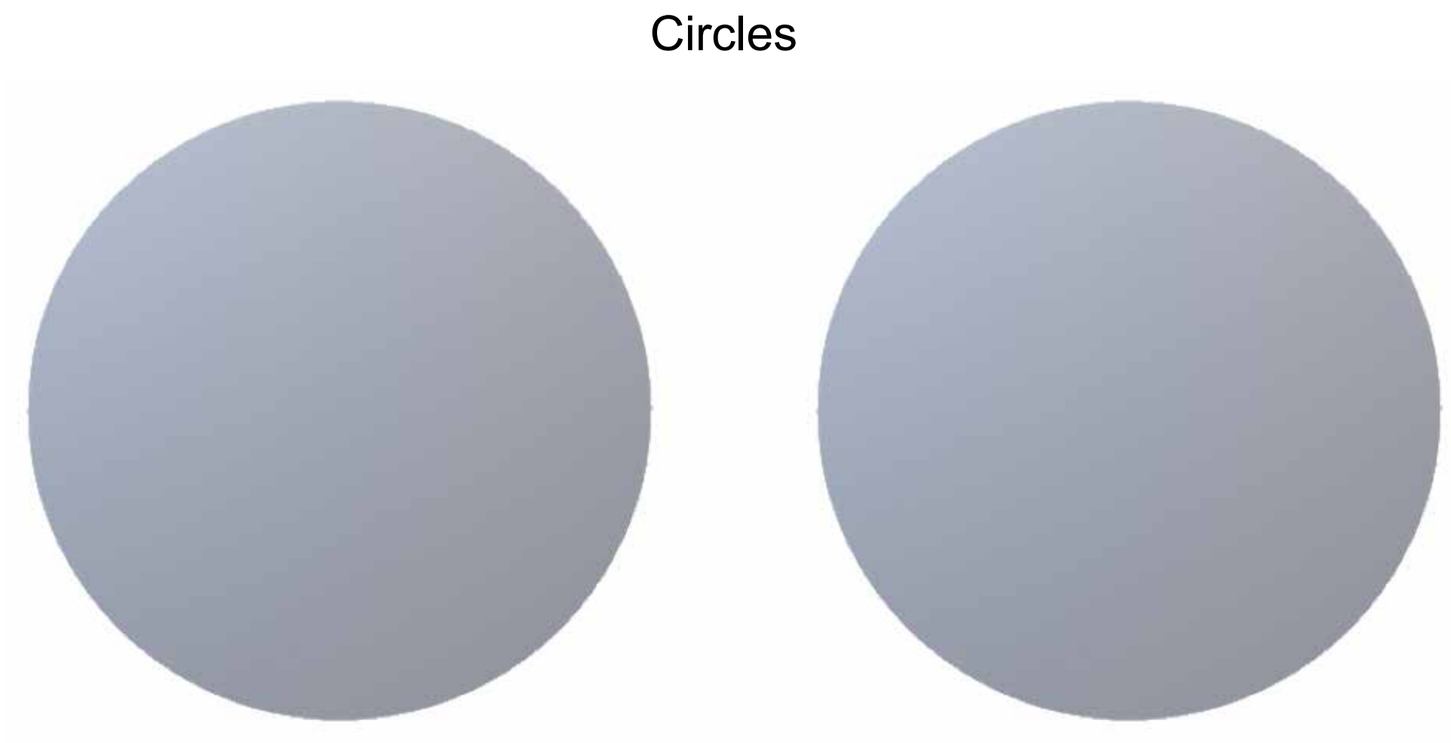
What Is a Condition Indicator?

A key step in predictive maintenance algorithm development is identifying *condition indicators*: features in your system data whose behavior changes in a predictable way as the system degrades. Condition indicators help you distinguish healthy operation from faulty. You extract them from preprocessed system data and use them for fault classification and remaining useful life (RUL) estimation.



A Visual Exercise

Let’s start with a visual exercise to understand how condition indicators work. What’s the difference between these two shapes?



It looks like there’s no significant difference because the two circles look almost the same.

A Visual Exercise - Continued

On the previous page, the shapes looked the same because you were looking at them from a certain angle, the top view. However, if you change your perspective, you can clearly see the differences between the two shapes and can identify them as a cone and a cylinder.

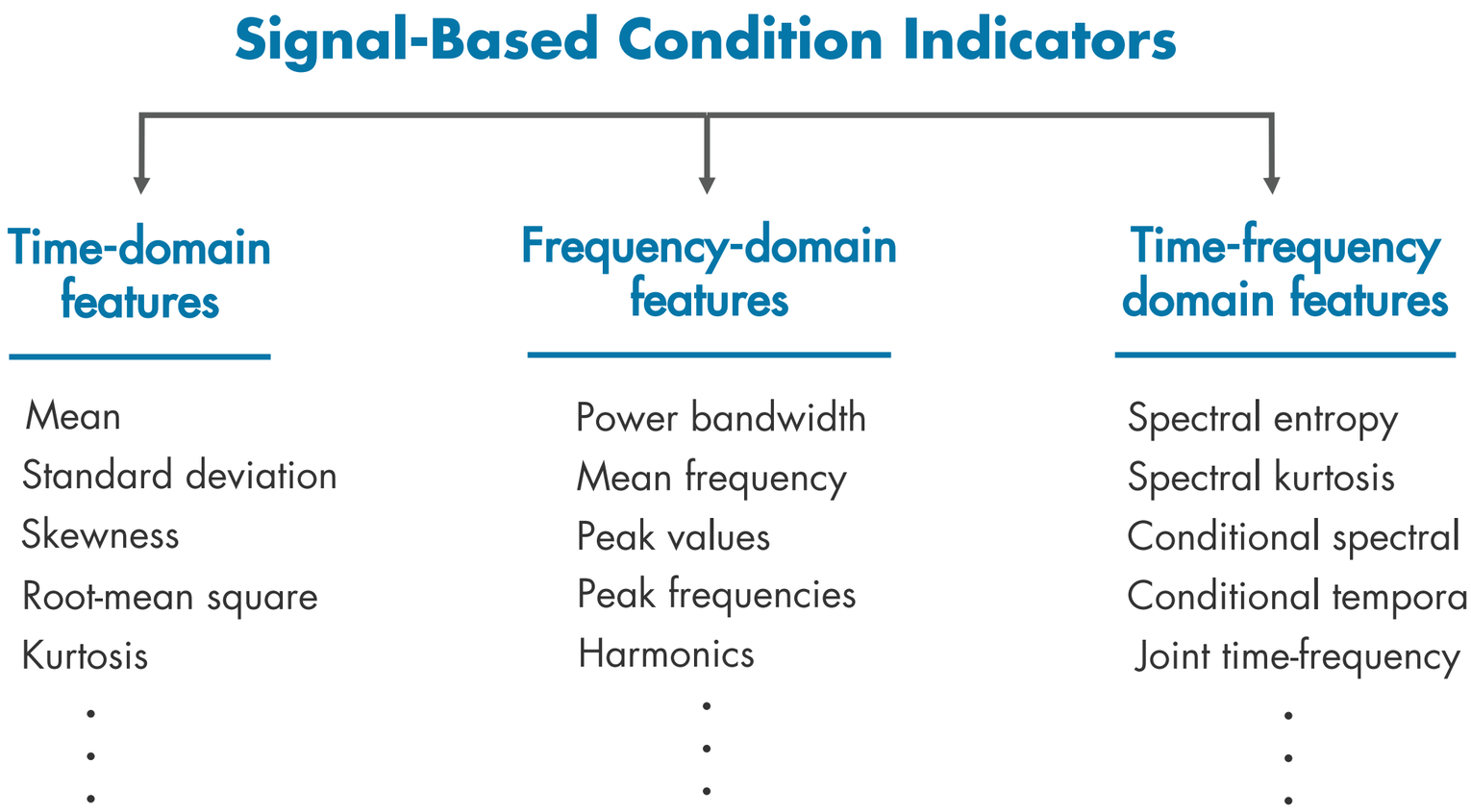
Cone

Cylinder

Similarly, when you look at raw measurement data from your machine, it's hard to tell healthy operation from faulty. But, using condition indicators, you're able to look at the data from a different perspective that helps you discriminate between healthy and faulty operation.

Feature Extraction Using Signal-Based Methods

You can derive condition indicators from data by using time, frequency, and time-frequency domain features:

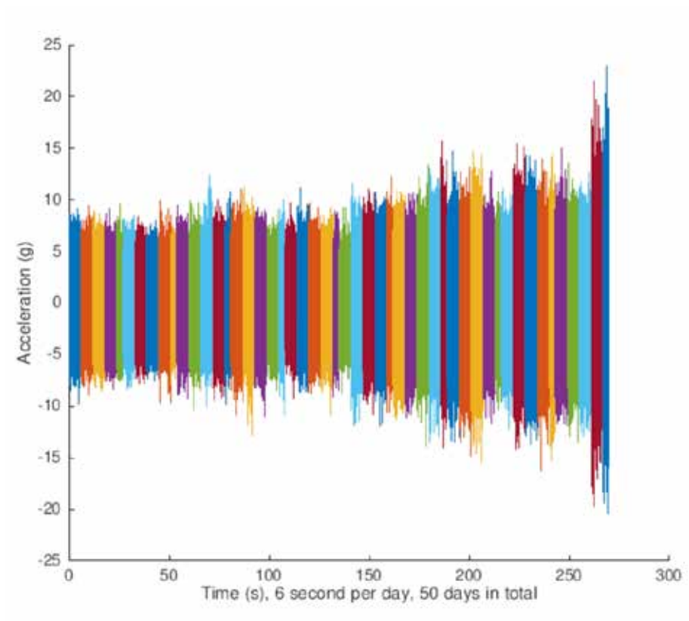


Feature Extraction Using Signal-Based Methods - Continued

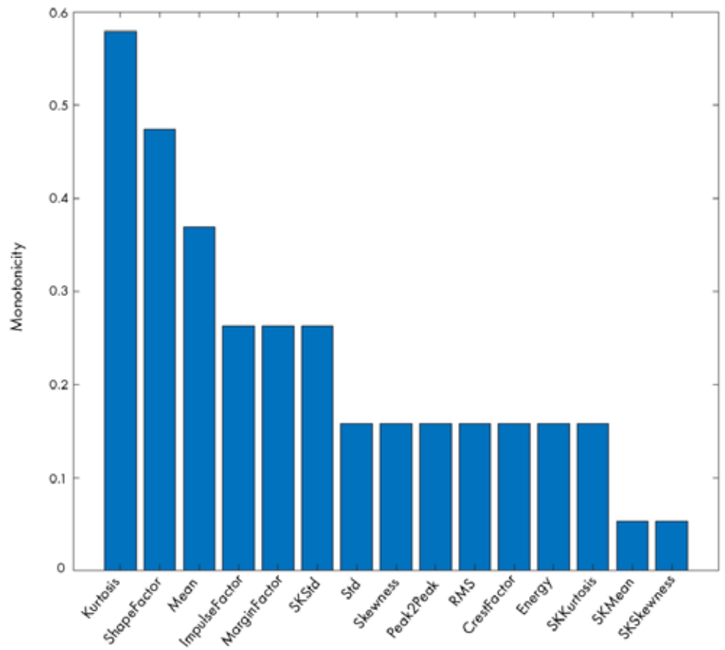
Time-Domain Features

For some systems, simple statistical features of time signals can serve as condition indicators, distinguishing faulty conditions from healthy. For example, the average value of a particular signal or its standard deviation might change as system health degrades. You can also use higher-order moments of the signal such as skewness and kurtosis. With such features, you can try to identify threshold values that distinguish healthy operation from faulty operation, or look for abrupt changes in the value that mark changes in system state.

Predictive Maintenance Toolbox™, an add-on product for MATLAB®, contains additional functions for computing time-domain features, demonstrated in the example *Turbine High-Speed Bearing Prognosis*.



The changing trend in time-domain vibration signals shows the degradation of a wind turbine high-speed shaft over 50 consecutive days.



The monotonicity graph shows the feature importance ranking for different time-domain and frequency-domain features.

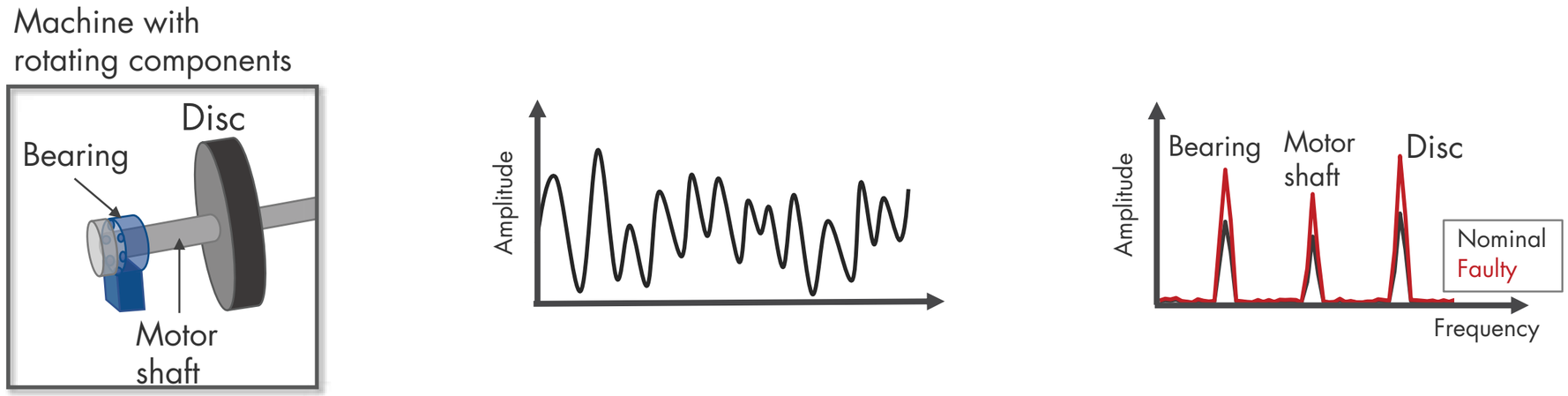
Feature Extraction Using Signal-Based Methods - Continued

Frequency-Domain Features

Sometimes, time-domain features alone are not sufficient to act as condition indicators, so you'll want to look at frequency-domain features as well.

Take a machine with rotational components and three vibration sources: bearing, motor shaft, and disc. If you look at the vibration data from the machine in the time domain, you see the combined effect of all the vibrations from these different rotating components. But by analyzing the data in the frequency domain, you can isolate different sources of vibration, as seen in the second plot. The peak amplitudes, and how much they change from nominal values, can indicate the severity of the faults.

More information on calculating frequency-domain condition indicators can be found in the example *Condition Monitoring and Prognostics Using Vibration Signals.*



When analyzing the vibration data from the machine in the time domain, the bearing, motor shaft, and disc all affect vibration amplitude. Using frequency-domain analysis, you can distinguish between different sources of vibration.

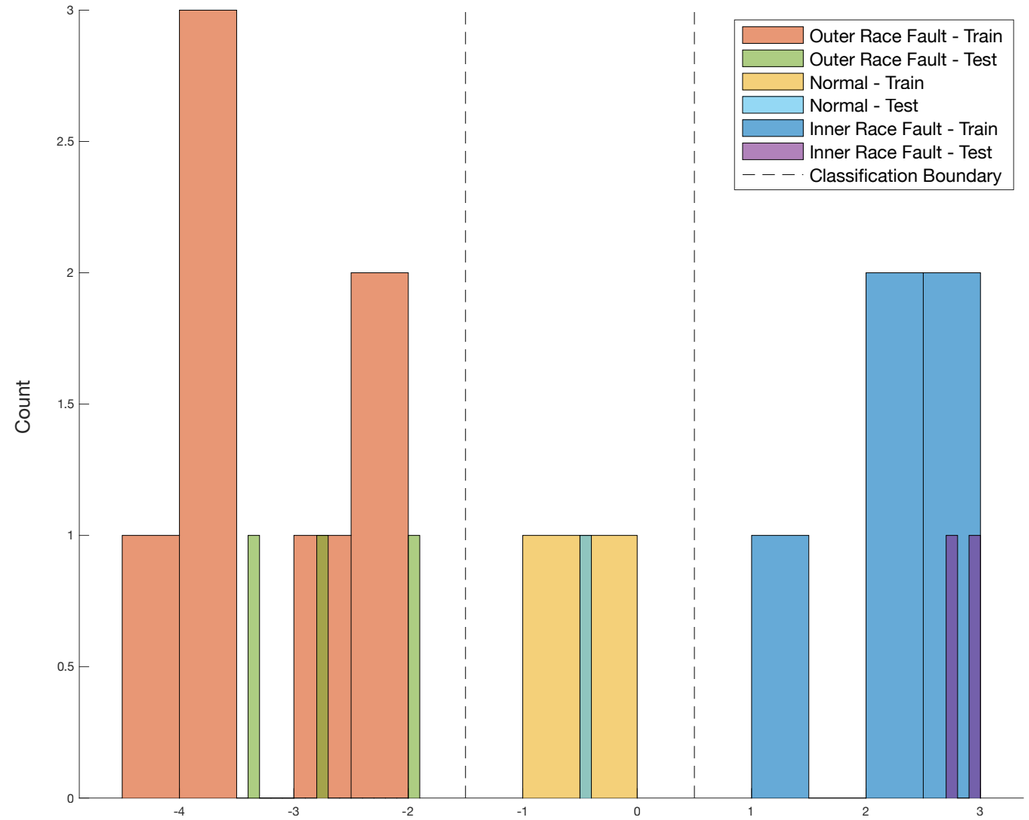
Feature Extraction Using Signal-Based Methods - Continued

Time-Frequency Domain Features

Another way to extract features is to perform time-frequency spectral analysis on the data, which helps characterize changes in the spectral content of a signal over time. Time-frequency domain condition indicators include features such as spectral kurtosis and spectral entropy.

The *Rolling Element Bearing Fault Diagnosis* example shows how to use kurtogram, spectral kurtosis, and envelope spectrum to identify different types of faults in rolling element bearings.

» *Learn more about time, frequency, and time-frequency domain features*



The histogram shows a clear separation between the three bearing conditions. The log ratio between the bandpass frequency inner and outer race amplitudes is a valid feature to classify bearing faults.

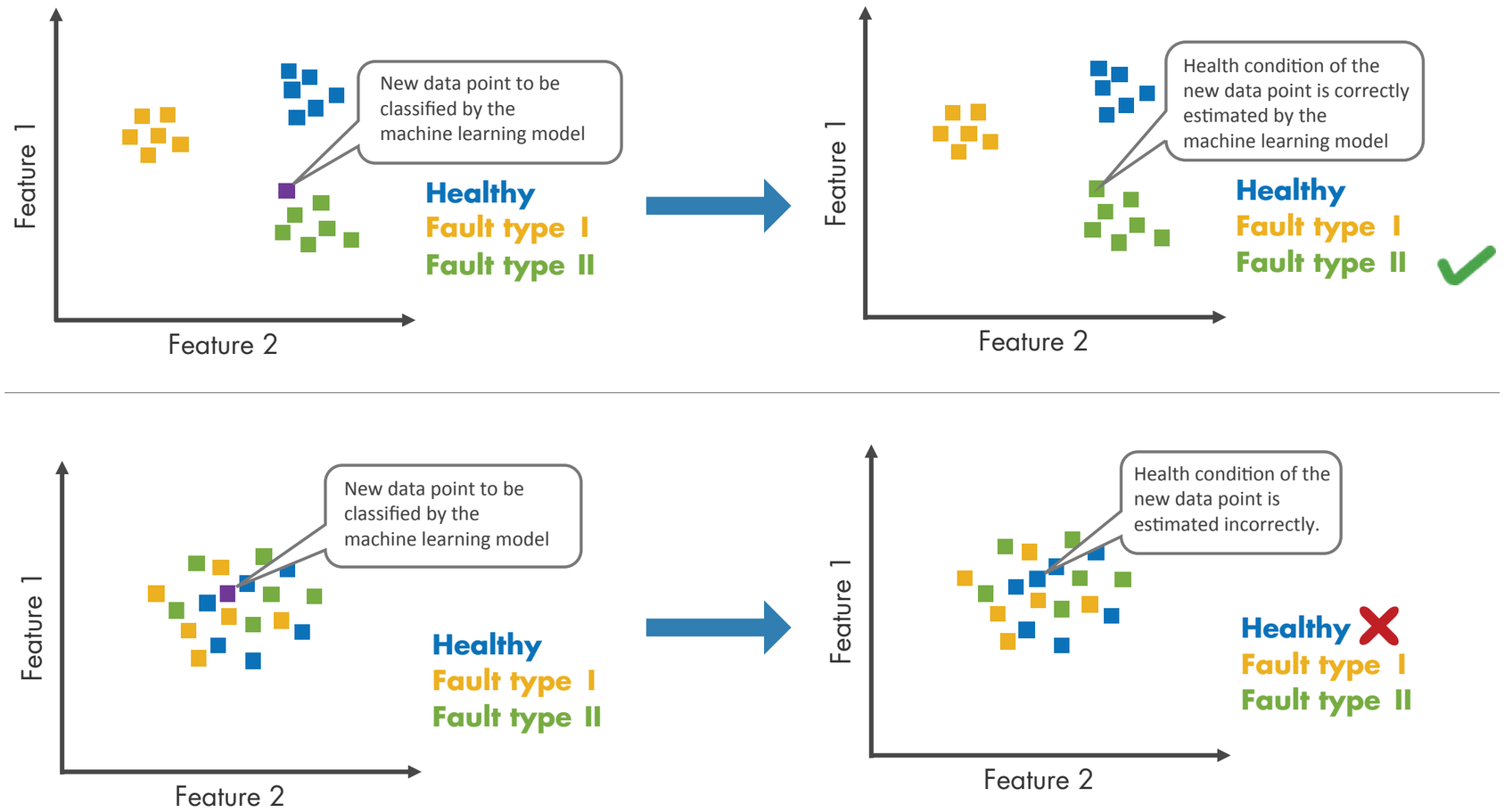
Predictive Maintenance Workflow

Now that you've looked at what condition indicators are, it's time to take a look at the steps involved in extracting the features for identifying condition indicators. Designing a predictive maintenance algorithm starts with collecting data from your machine under different operating conditions and fault states. The raw data is then preprocessed for cleaning it up and bringing it into a form from which condition indicators can be extracted. Feature extraction looks for features that are distinctive, meaning they uniquely define healthy operation and different fault types. These features will be your *condition indicators.*

Using the extracted features, you can train a machine learning model for fault classification and remaining useful life estimation. You can then deploy your algorithm and integrate it into your systems for machine monitoring and maintenance.

What Are Distinctive Features and Why Are They Important?

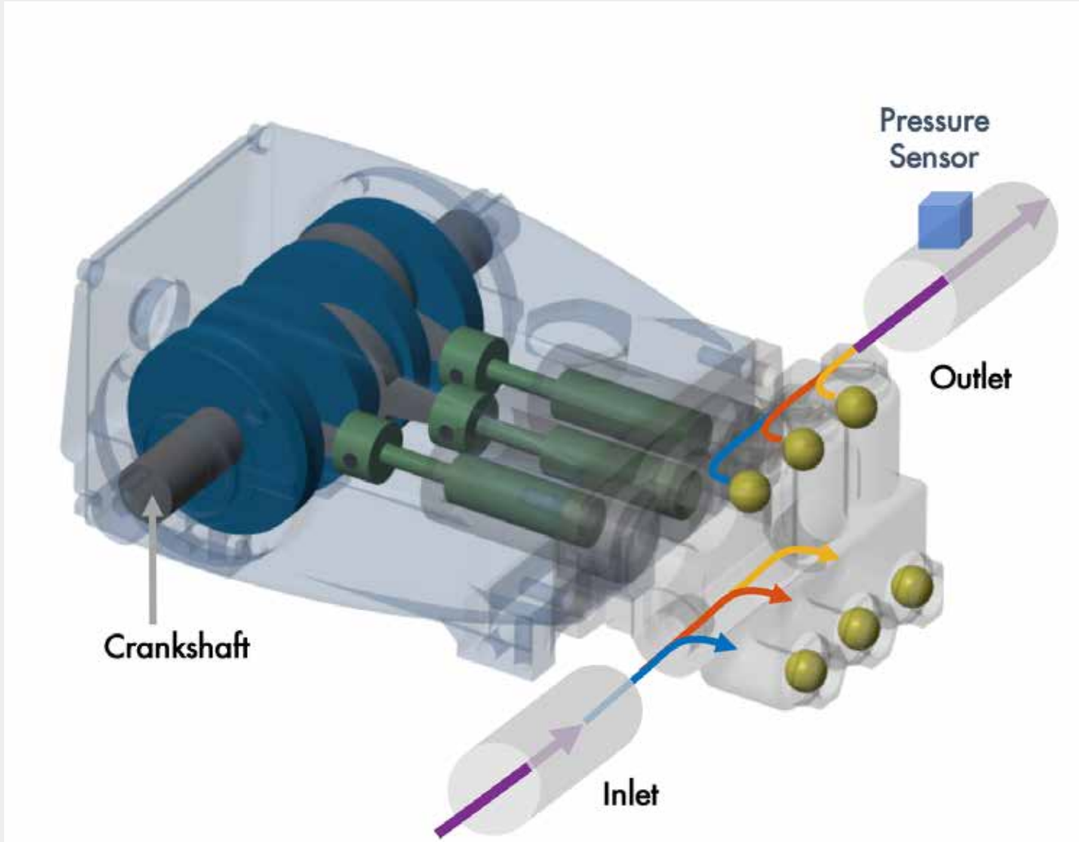
Once you identify some useful features, you can use them to train a machine learning model. If the selected set of features is distinctive, the model can correctly estimate the machine's current condition when you feed new data from the machine to the model.



Example: The Triplex Pump

This example uses a triplex pump to demonstrate the workflow. The pump has a motor that turns the crankshaft that in turn drives three plungers. The fluid gets sucked into the inlet and discharged through the outlet, where the pressure is measured by a sensor. Faults that can develop in such a pump include:

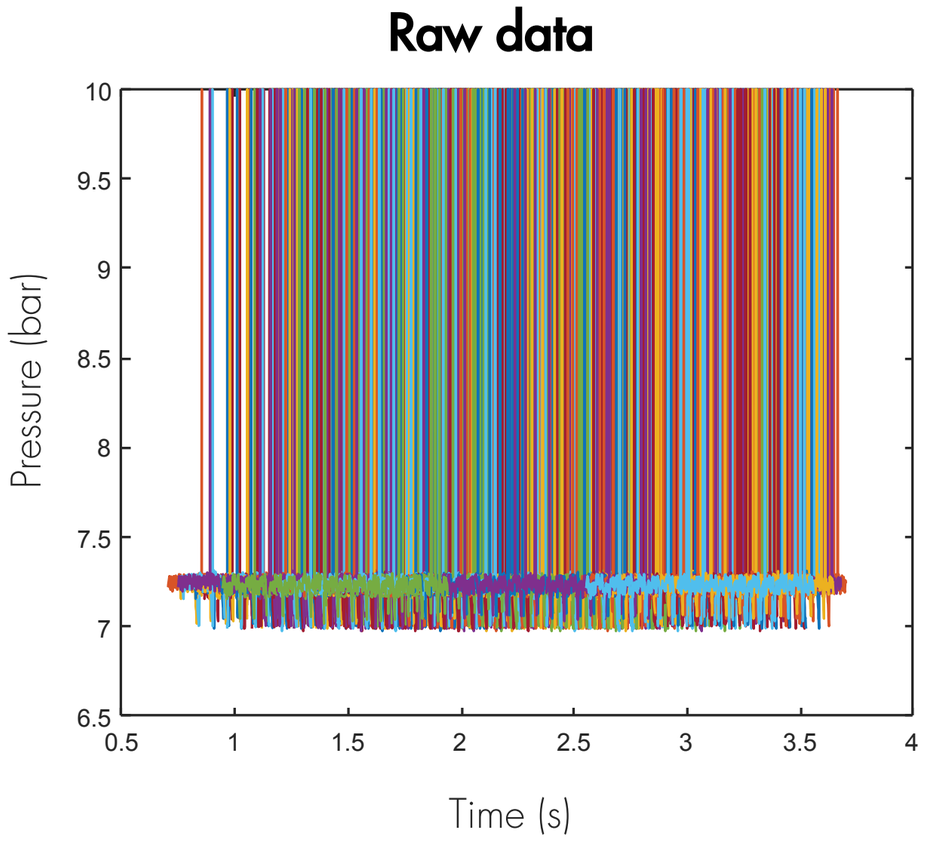
- Seal leakage
- Blocked inlet
- Worn bearing



Acquiring Data

This pressure data includes one-second-long measurements taken at steady state from normal operation, all three fault types, and also their combinations:

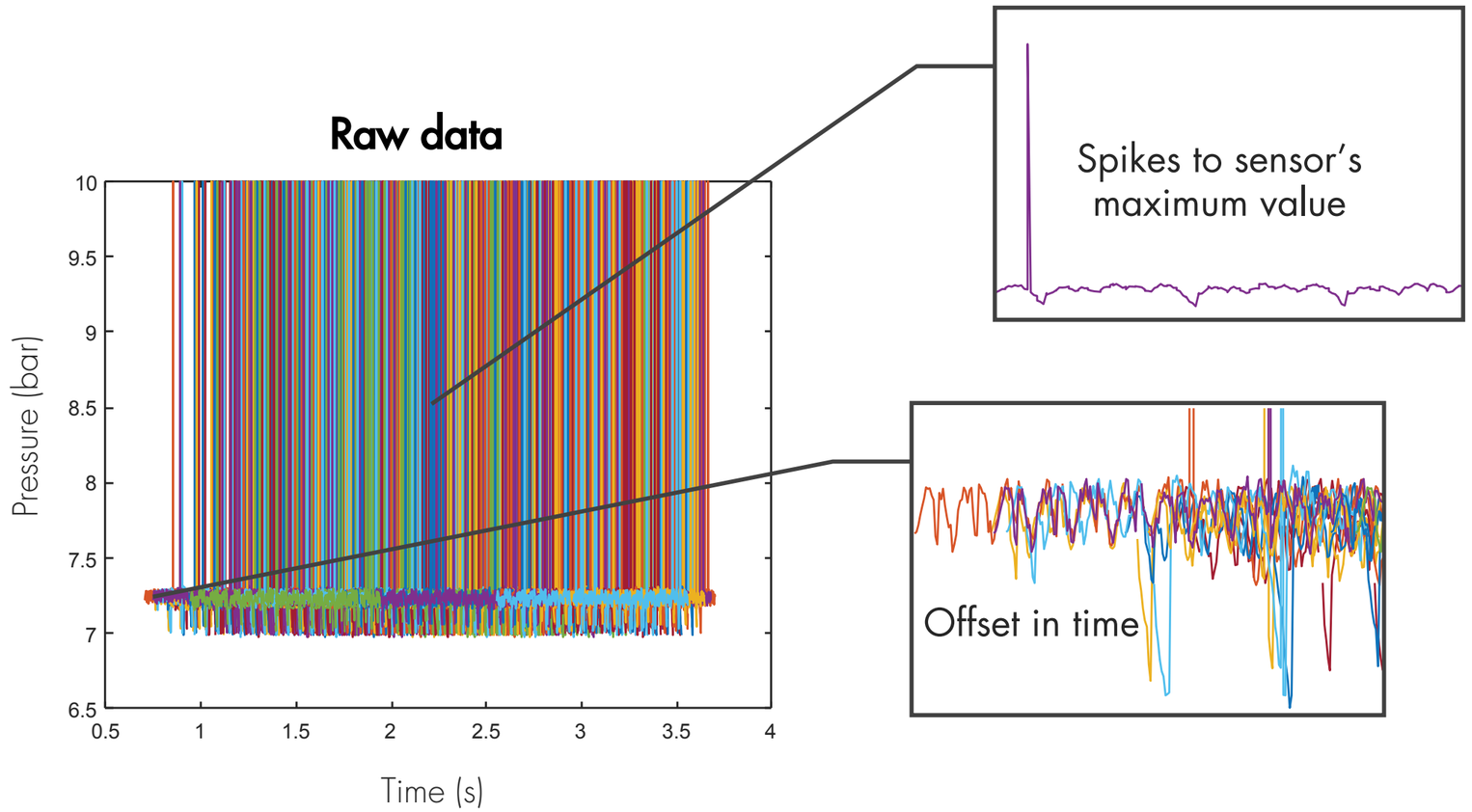
- Healthy
- Blocked inlet
- Worn bearing
- Seal leakage
- Blocked inlet, worn bearing
- Seal leakage, worn bearing
- Seal leakage, blocked inlet



Plot of the pressure data that has been collected from the triplex pump.

Preprocessing Data

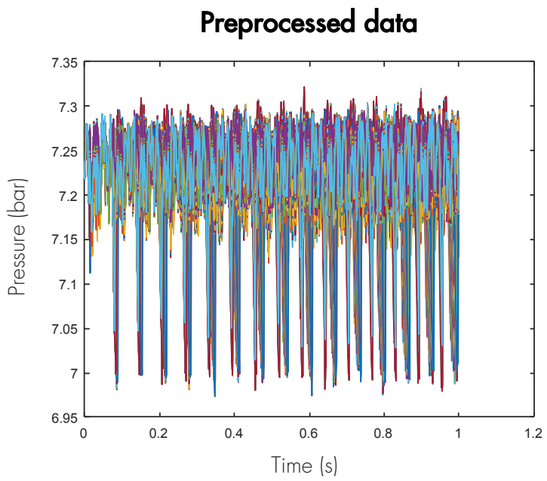
You need to bring the data into a usable form to extract condition indicators. The raw data is noisy and has spikes up to the sensor's maximum value. It's also offset in time even though the durations of the measurements are the same.



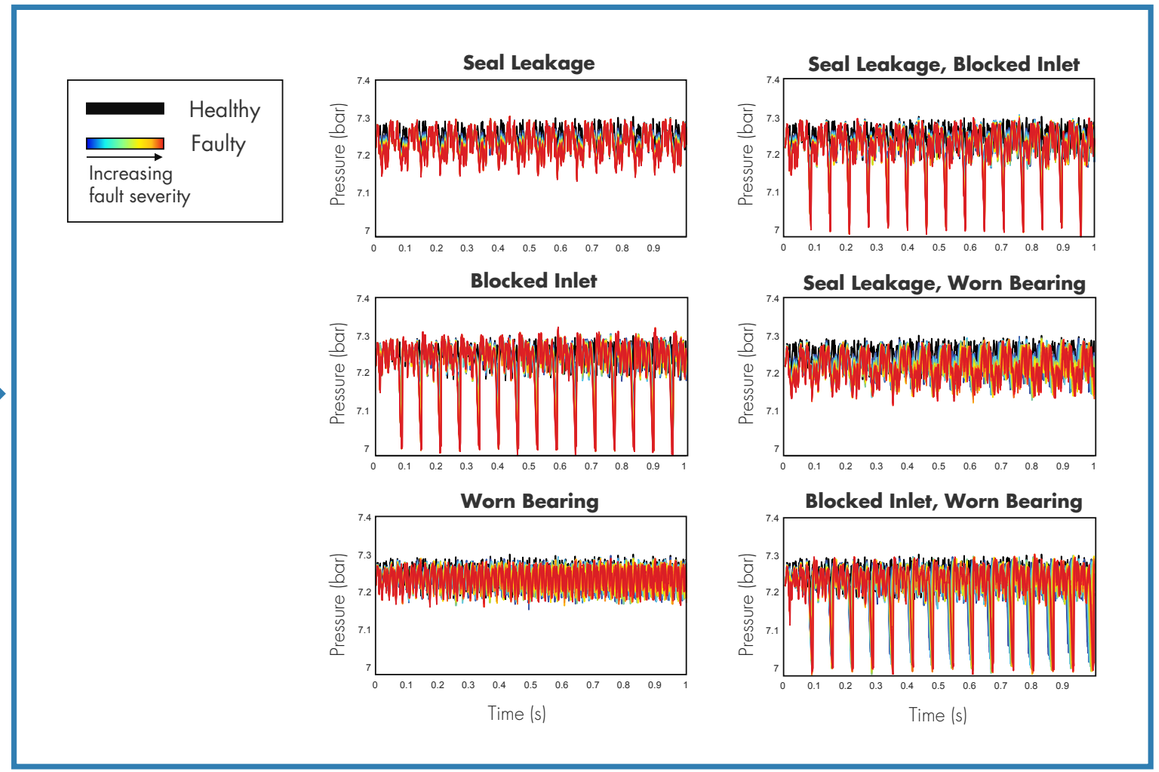
Preprocessing Data - Continued

MATLAB has *functions* to help smooth, denoise, and perform other preprocessing techniques on signal data.

The processed data includes all the healthy and faulty conditions. In order to investigate different fault types and their combinations, you can plot them individually. The first thing to notice on these plots is the cyclical behavior of the time-domain pressure signal. Next, take a look at a plot of a shorter time period on the next page to see what's happening in each cycle more clearly.



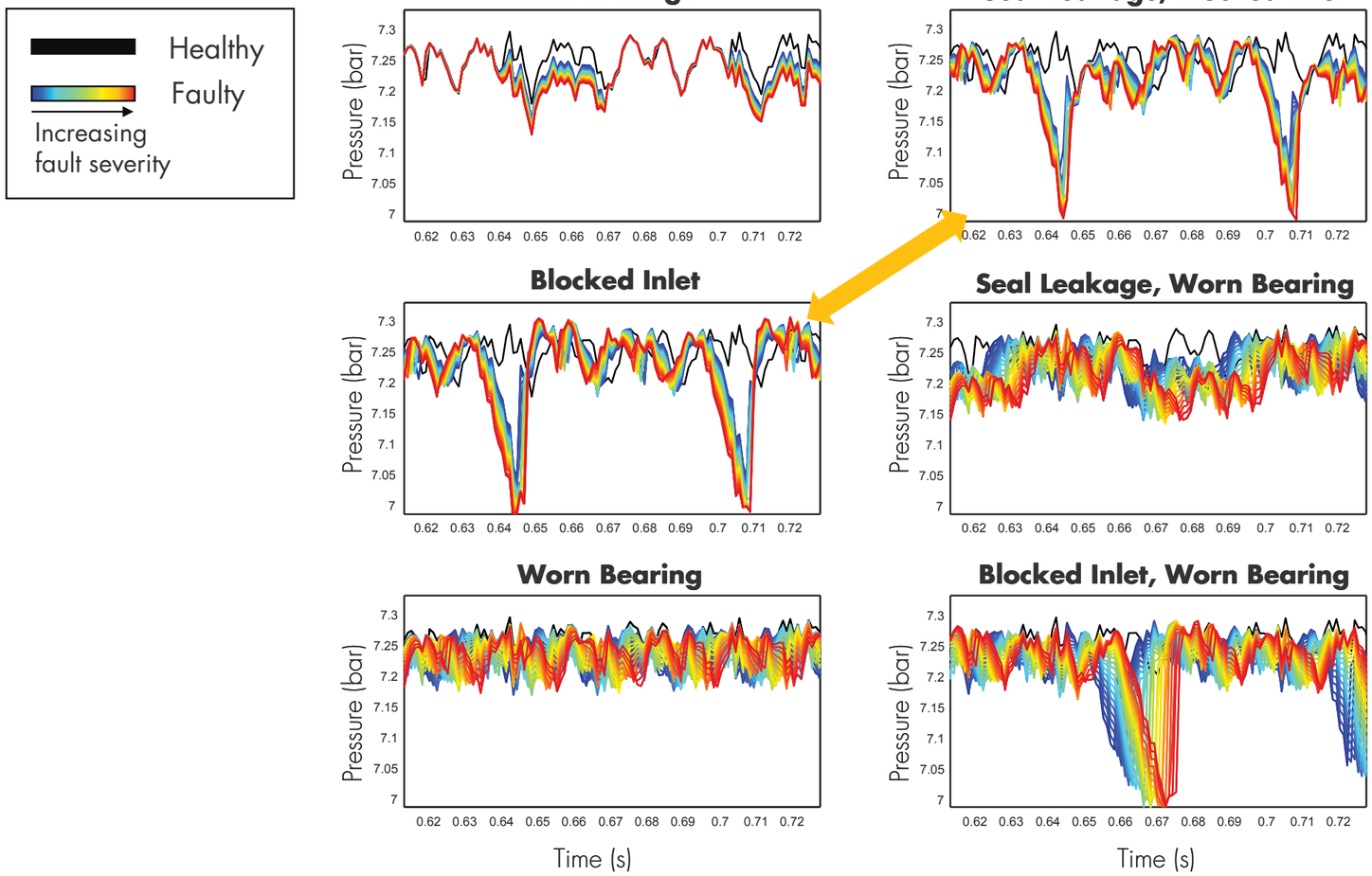
Graph Data Mapped to 6 Plots



Preprocessing Data - Continued

These plots provide a more detailed look at the pressure signal for different types of faults. The change in the pressure data as the pump deteriorates is reflected with changing colors from dark blue to red indicating increasing fault severity. Now the question is: Can you distinguish the black line, the healthy operation, from the rest of the data on each plot? And, can you identify the unique differences between each set of colored lines? Notice how the pressure data looks very similar for the “seal leakage, blocked inlet” and “blocked inlet” faults.

Now let’s look at some of the time-domain features to identify condition indicators to help you distinguish between fault types.

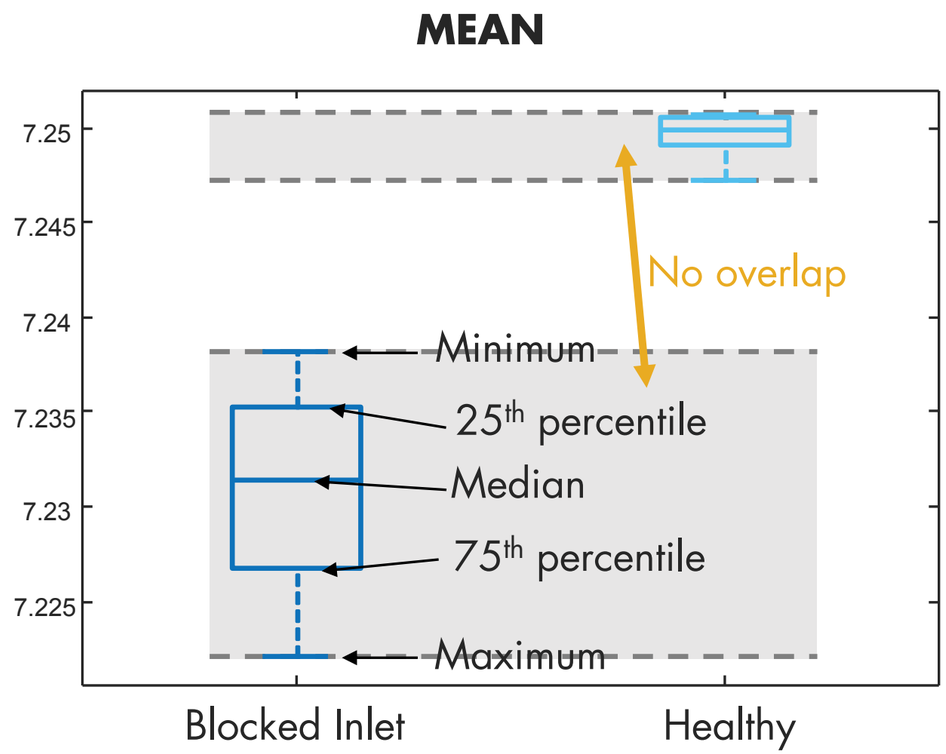


Using Time-Domain Features for Identifying Condition Indicators

Use trial and error to see how each of the following set of common time-domain features performs: *Mean*, *Variance*, *Skewness*, and *Kurtosis.*

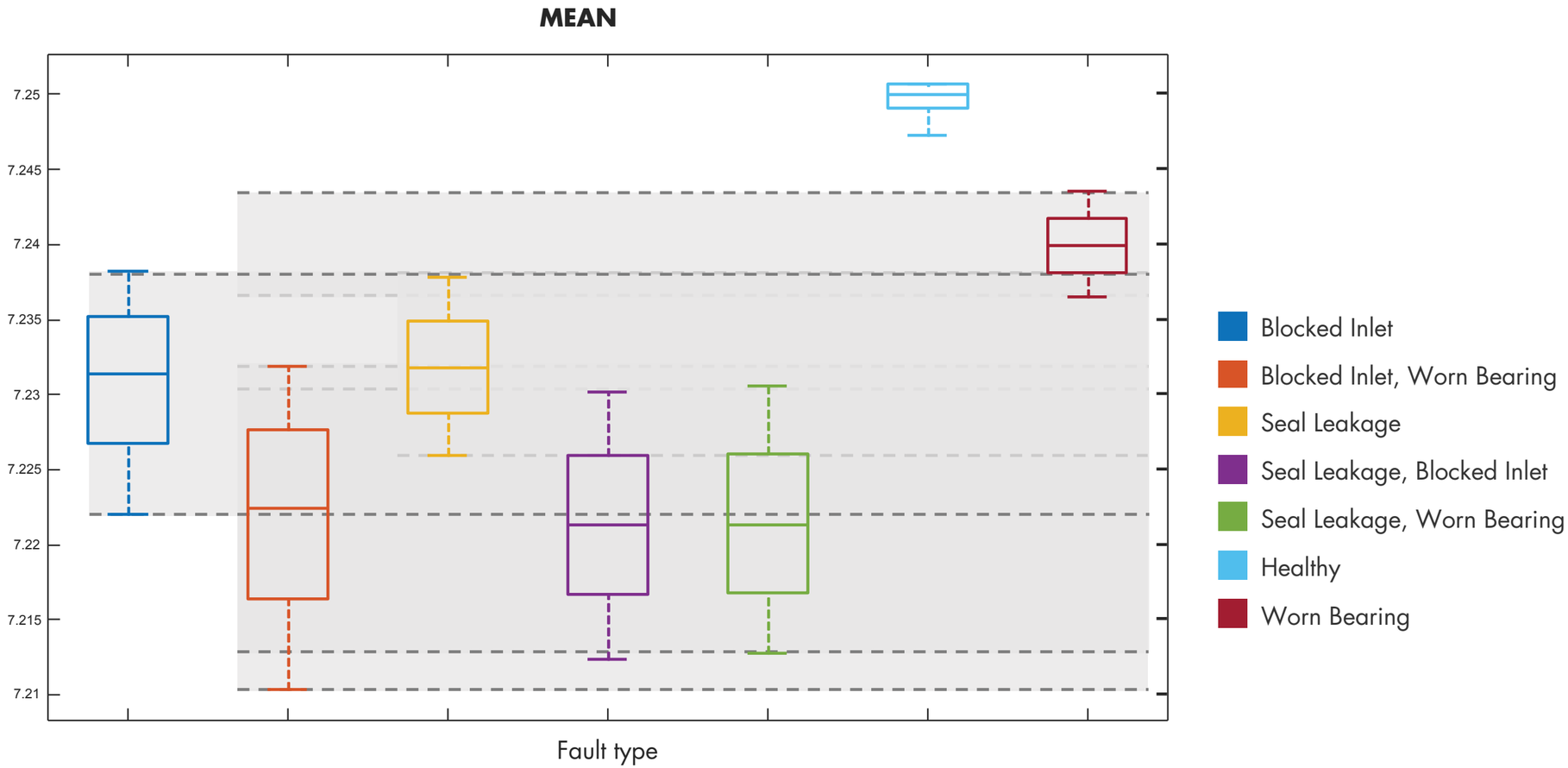
One way to understand if these condition indicators can differentiate between types of faults is to investigate them using a boxplot. First, plot a single feature, such as the mean, for the healthy condition and blocked inlet fault.

The boxes don’t overlap in the plot. This means there’s a difference between these data groups. By using the mean of the pressure data, you can easily distinguish the blocked inlet fault from healthy condition.



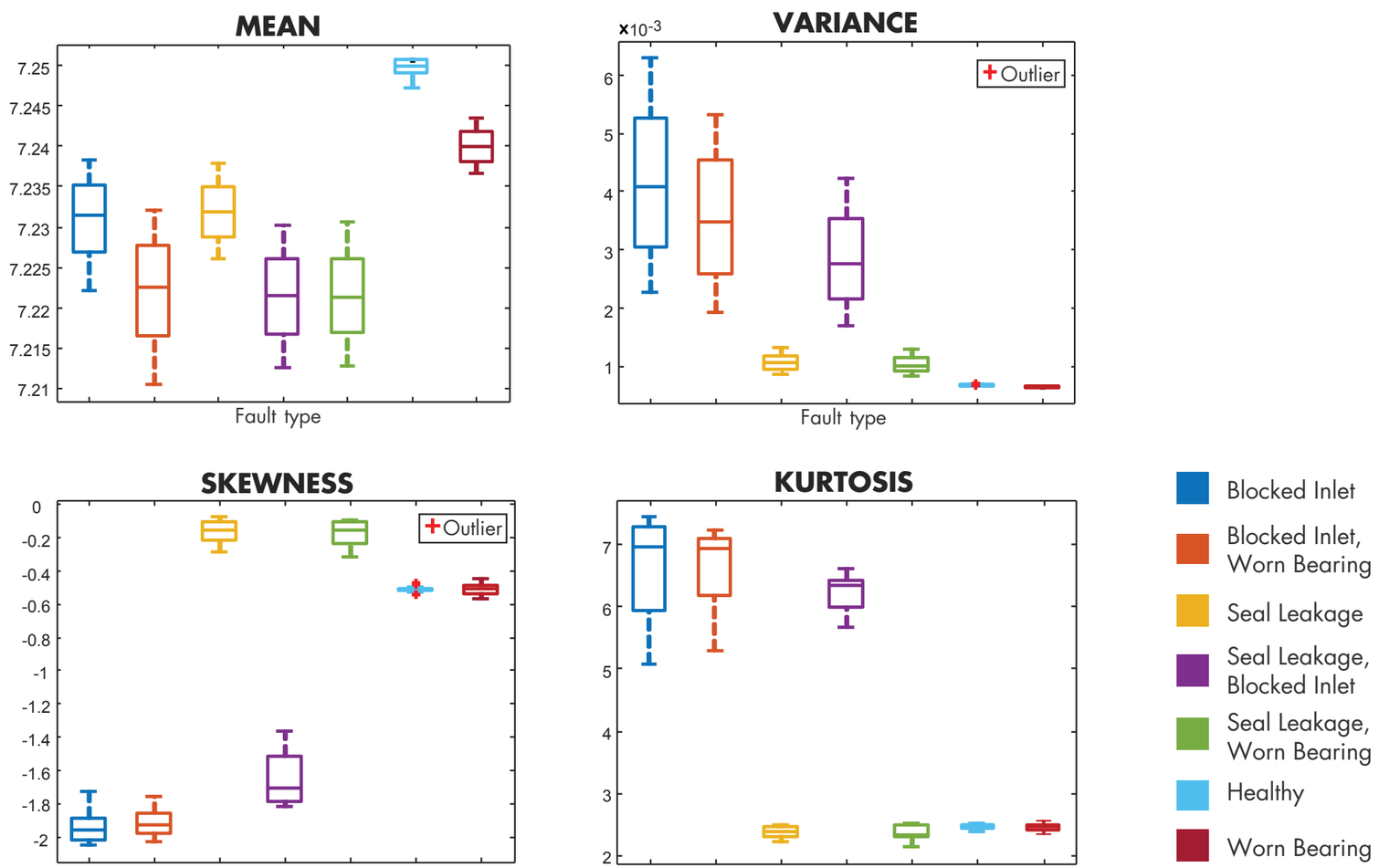
Using Time-Domain Features for Identifying Condition Indicators - Continued

Things change when you add the datasets for other fault types as well. You're not able to distinguish between all the fault types as some of them overlap. Due to this overlapping, the mean on its own is not enough to set fault types apart.



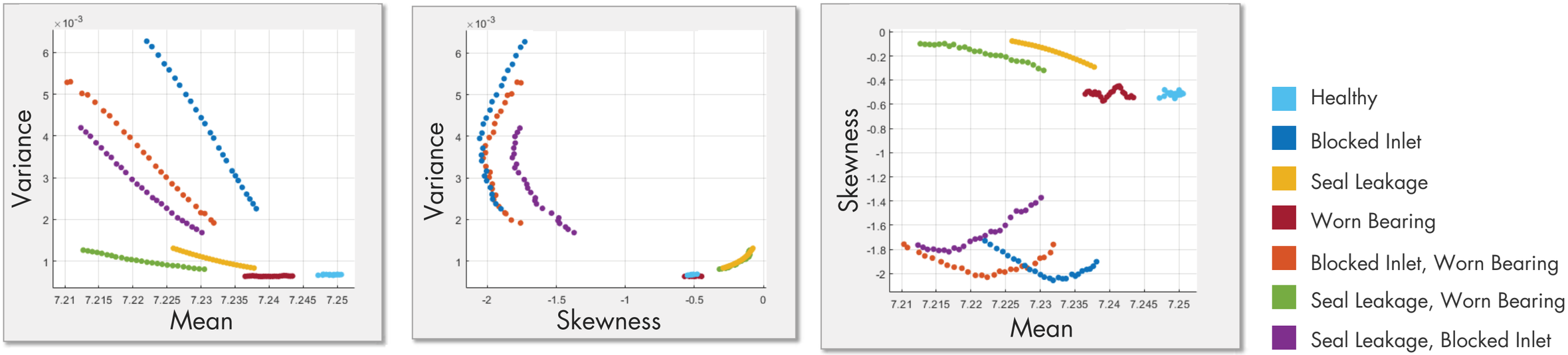
Using Time-Domain Features for Identifying Condition Indicators - Continued

If you try this with other features as well, you end up at the same conclusion: A single condition indicator is not sufficient to classify the faulty behavior, especially when you have multiple faults.



Using Time-Domain Features for Identifying Condition Indicators - Continued

Below is a scatter plot of a combination of the features: mean, variance, and skewness. Notice how well the variance versus mean plot distinguishes between different types of faults.



You can immediately see that two condition indicators are better than one for separating different faults. You can try different pairs of features to see which ones are better at classifying faults.

Using Time-Domain Features for Identifying Condition Indicators - Continued

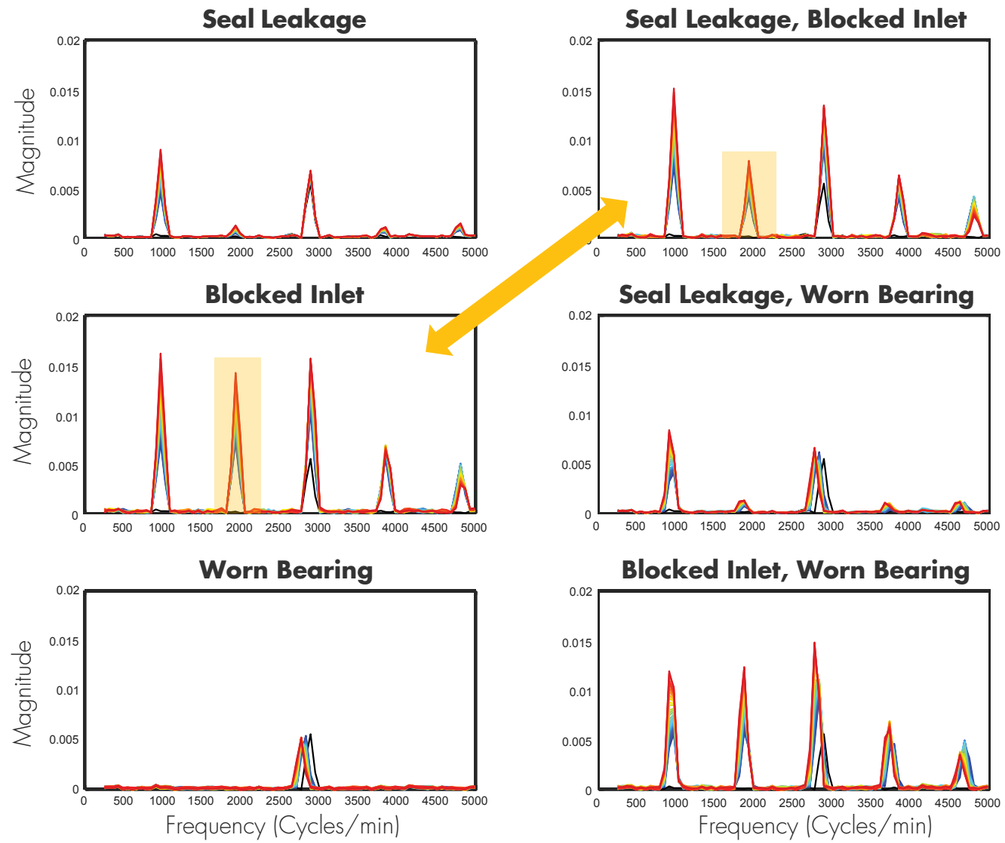
Frequency-domain analysis is important in analyzing periodic data and data acquired from a machine with rotating components; let's see if you can extract additional features by analyzing your data in the frequency domain.

What differentiates these plots from each other are the peaks and the peak frequencies, so they can serve as condition indicators. With time-domain features, it was hard to distinguish between the "seal leakage, blocked inlet" and "blocked inlet" faults because of the similarity of the datasets. By looking at the data in the frequency domain, you can see that the peak values at the highlighted frequency range will help you successfully separate these two faults.

In MATLAB, you can use `fft` function to compute the fast Fourier transform of a signal and analyze it in the frequency domain. You can then use the `findpeaks` function to extract the peaks and peak frequencies from the FFT signal.

In summary, the features you should use to train a machine learning model in this example include:

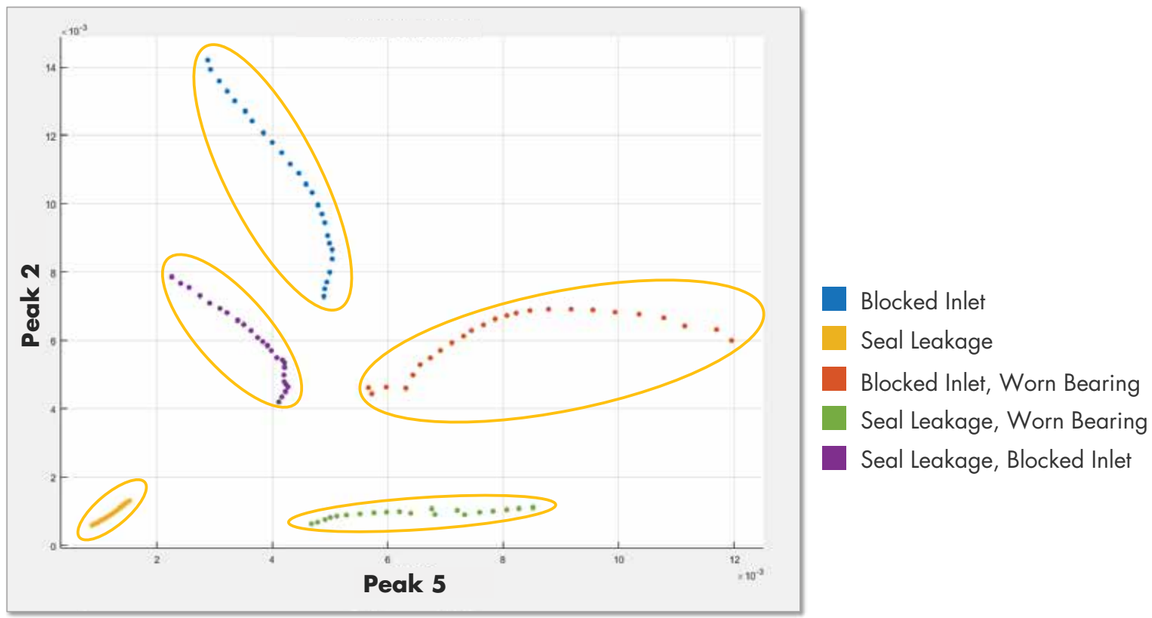
- **Time-domain features:** Mean, variance, skewness, kurtosis
- **Frequency-domain features:** Peaks and peak frequencies



Using Time-Domain Features for Identifying Condition Indicators - Continued

After selecting the frequency-domain features, try to perform an analysis like you did with the time-domain features. The below plot shows the second and fifth peaks with respect to each other.

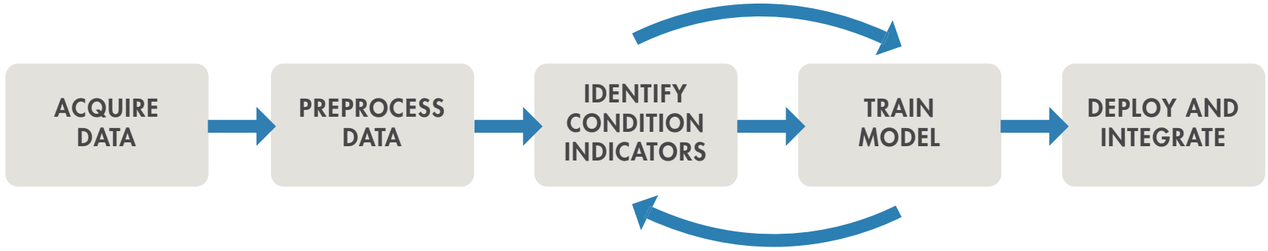
These features effectively separate different groups, which are highlighted with yellow circles. This means that the selected features are distinctive and good candidates for training a machine learning model.



Note that when you're investigating these features, not only are you looking for different clusters, but you also want them to be further away from each other. This makes it easier for the trained models to identify new data points.

The previous page shows plots of the peaks for each of the faults, with the faults in color and the healthy condition in black. Notice that the "worn bearing" plot contains only Peak 3 for the worn bearing and healthy conditions. This is why these conditions don't show up on a plot representing Peaks 2 and 5. This is another reason why we need multiple features to effectively separate the different groups.

Training the Model

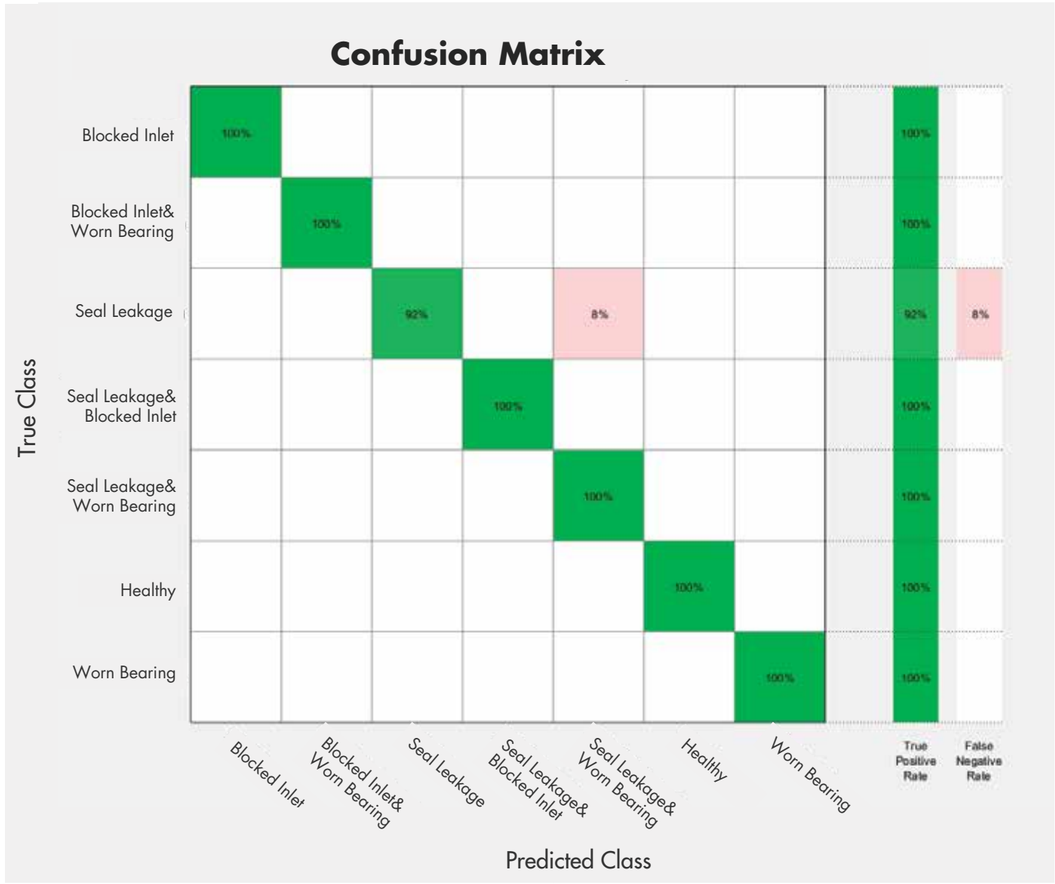


After extracting the condition indicators, you can train a *machine learning model* with the extracted features and check the accuracy of the trained model with a confusion matrix. The confusion matrix at right shows the results of one the best-performing classifiers that has been trained with the extracted features. The *Classification Learner app* in MATLAB helps you find the best classifier for your dataset quickly.

The plot shows the true positive rates in green and false negative rates in red.

If you're satisfied with the accuracy of your machine learning model, you can continue with deploying your predictive maintenance algorithm and integrating it into your system. Otherwise, you should revisit the feature extraction step of the predictive maintenance workflow and try training machine learning models with different sets of features, as highlighted with the arrows in the workflow chart.

You may be wondering, how many features are enough to train a machine learning model? Unfortunately, there's no magic number. Just remember that machine learning models can benefit from a high-dimensional set of features that are distinctive and can effectively differentiate fault types.



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Part 3: Estimating Remaining Useful Life

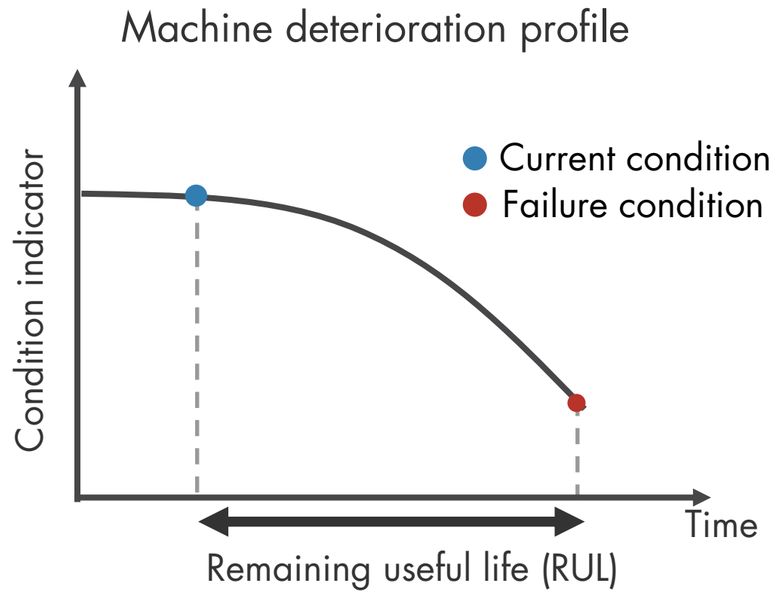
MathWorks®

What Is Remaining Useful Life?

One of the goals of predictive maintenance is to estimate the remaining useful life (RUL) of a system. RUL is the time between a system's current condition and failure. Depending on your system, time can be represented in terms of days, flights, cycles, or any other quantity.

On the plot, we see the deterioration path of a machine over time.

This ebook explores three common models used to estimate RUL (similarity, survival, and degradation) and then walks through the RUL workflow with an example using a similarity model.



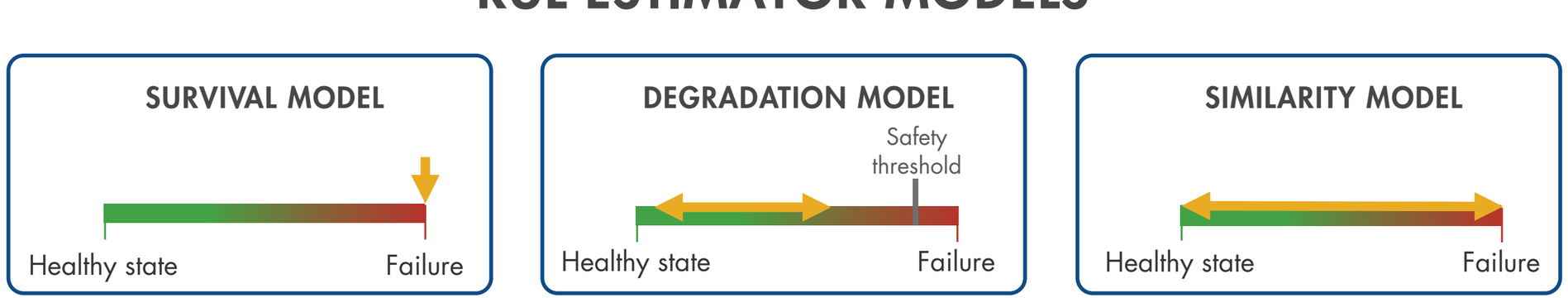
Three Common Ways to Estimate RUL

There are three common models used to estimate RUL: similarity, survival, and degradation. Which model should you use? It depends on how much information you have.

Use a *survival model* if you have data only from time of failure rather than complete run-to-failure histories.

Use a *degradation model* if you have some data between a heathy state and failure, and you know a safety threshold that shouldn't be exceeded.

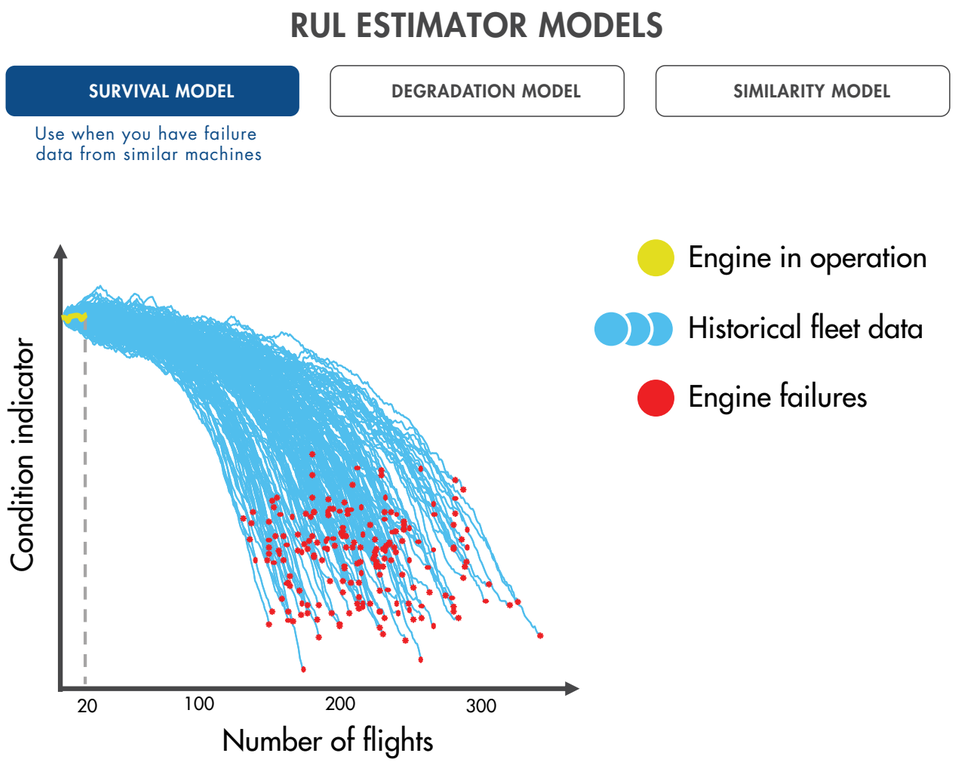
Use a *similarity model* if your data spans the full degradation of a system from a healthy state to failure.



Find more detailed information on *RUL Estimator Models* used in predictive maintenance.

The following aircraft engine example illustrates how estimator models work.

The Working Principle of RUL Estimator Models: The Survival Model



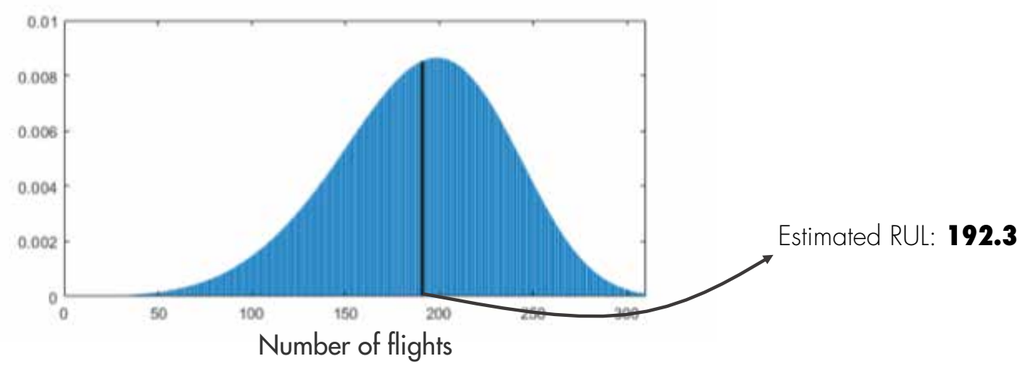
In this example, you want to figure out how many flights the engine can operate until its parts need repair or replacement.

The yellow line on the plot represents your engine, which has been in operation for 20 flights. The blue lines represent the data from a fleet with the same type of engine. The red marks indicate when the engines failed.

If you don't have the complete histories from the fleet, but you do have the failure data, then you can use survival models to estimate RUL.

You can determine how many engines failed after a certain number of cycles (number of flights), and you also know how many flights the engine has been in operation. The survival model uses a probability distribution of this data to estimate the remaining useful life.

Probability density function for the RUL estimation after 20 flights

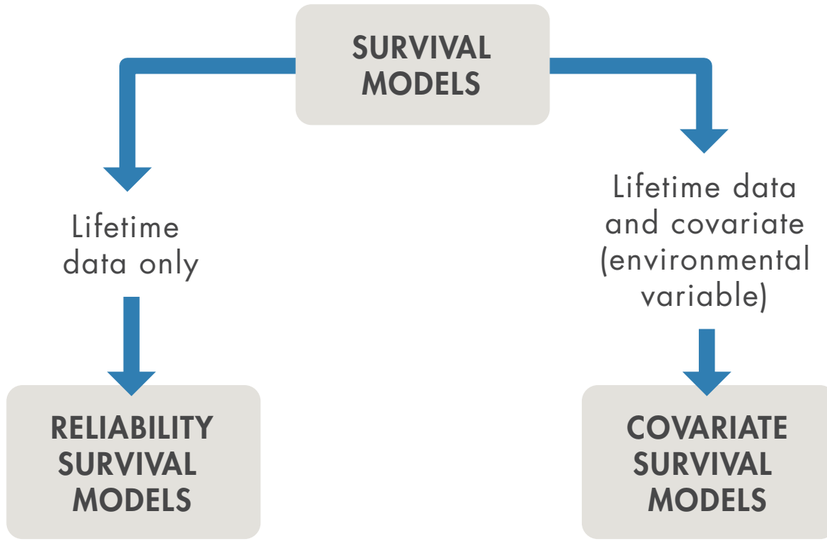


The Working Principle of RUL Estimator Models: The Survival Model in MATLAB

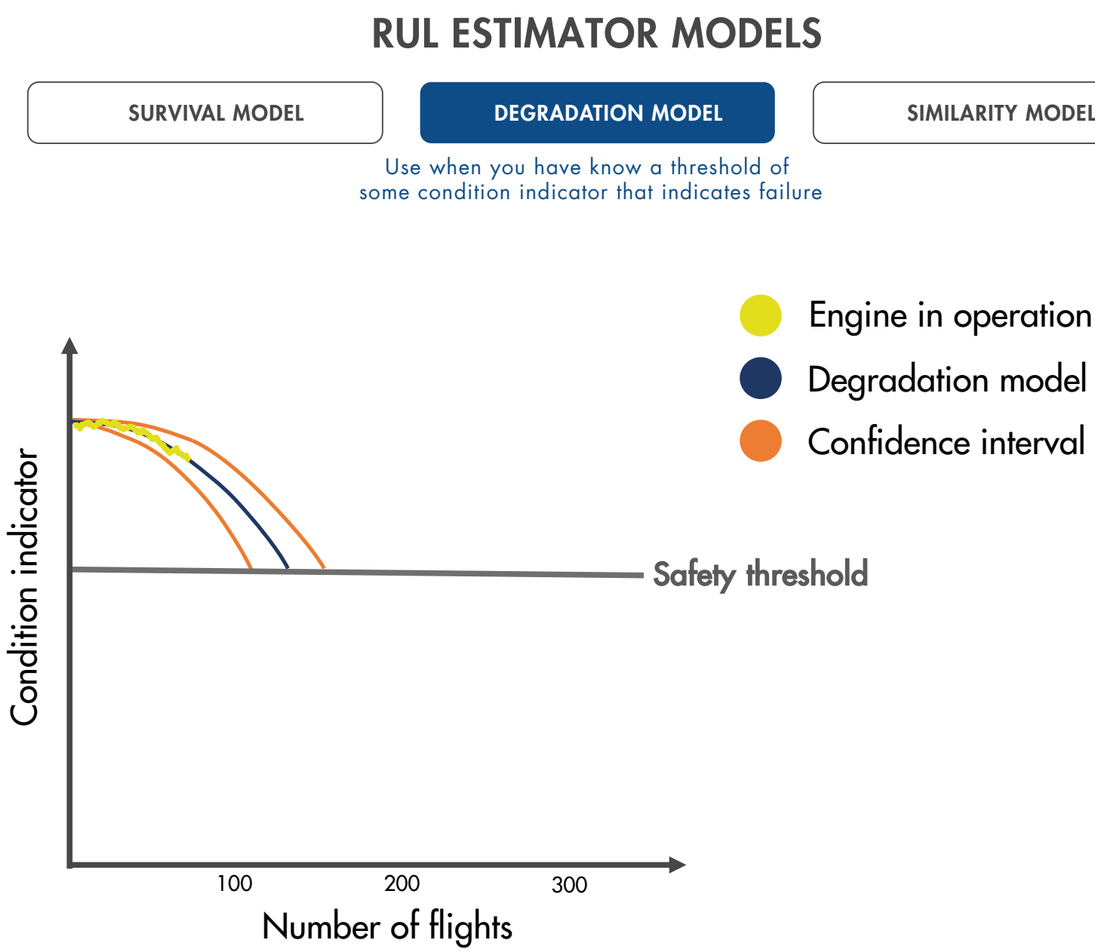
Survival analysis is a statistical method used to model time-to-event data. It is useful when you do not have complete run-to-failure histories, but instead have:

Only data about the life span of similar components. For example, you might know how many miles each engine in your ensemble ran before needing maintenance. In this case, you use the MATLAB® model `reliabilitySurvivalModel`. Given the historical information on failure times of a fleet of similar components, this model estimates the probability distribution of the failure times. The distribution is used to estimate the RUL of the test component.

Both life spans and some other variable data (covariates) that correlates with the RUL. Covariates include information such as the component provider, regimes in which the component was used, or manufacturing batch. In this case, use the MATLAB model `covariateSurvivalModel`. This model is a proportional hazard survival model that uses the life spans and covariates to compute the survival probability of a test component.



The Working Principle of RUL Estimator Models: The Degradation Model



In some cases, no failure data is available from similar machines. But you may have knowledge about a safety threshold that shouldn't be crossed as this may cause failure. You can use this information to fit a degradation model to the condition indicator, which uses the past information from our engine to predict how the condition indicator will change in the future. This way, you can statistically estimate how many cycles there are until the condition indicator crosses the threshold, which helps you estimate the remaining useful life.

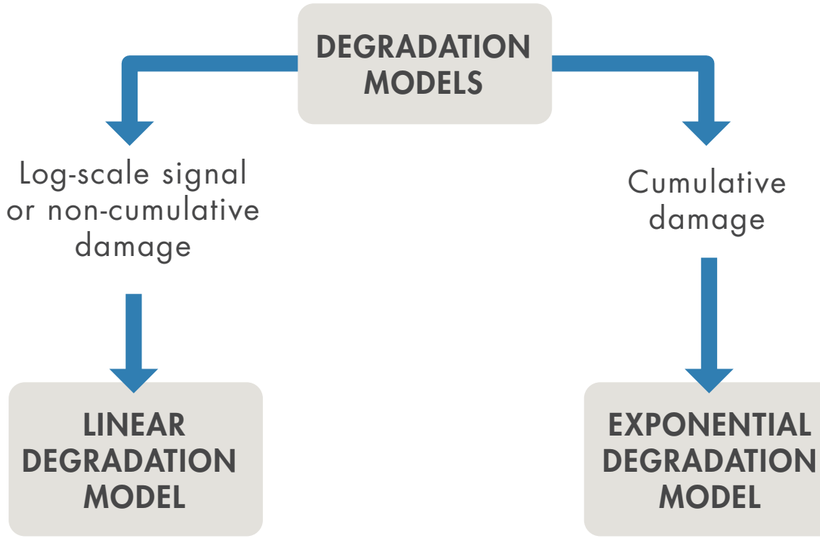
The Working Principle of RUL Estimator Models: The Degradation Model in MATLAB

Degradation models estimate RUL by predicting when the condition indicator will cross a prescribed threshold. These models are most useful when there is a known value of your condition indicator that indicates failure. The two available degradation model types in Predictive Maintenance Toolbox™ are:

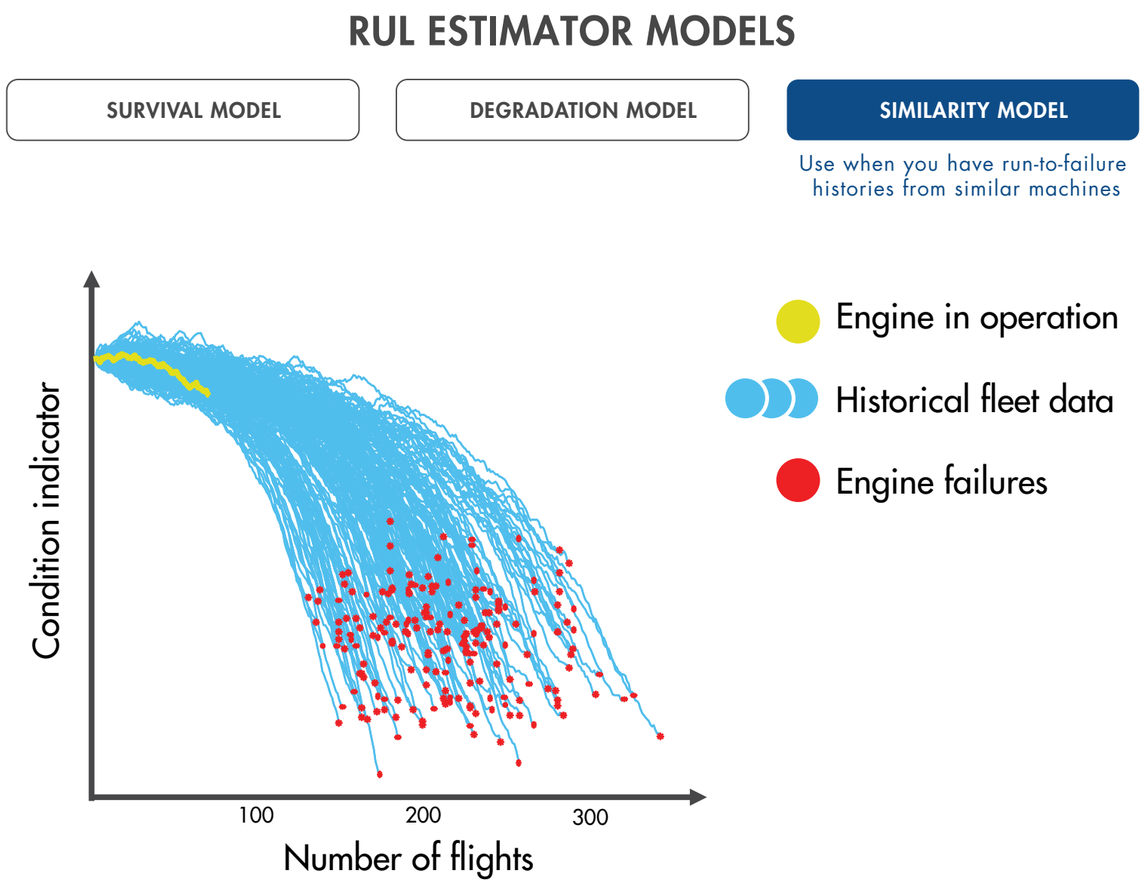
Linear degradation model (`linearDegradationModel`) describes the degradation behavior as a linear stochastic process with an offset term. Linear degradation models are useful when your system does not experience cumulative degradation.

Exponential degradation model (`exponentialDegradationModel`) describes the degradation behavior as an exponential stochastic process with an offset term. Exponential degradation models are useful when the test component experiences cumulative degradation.

Degradation models work with a single condition indicator. However, you can use principal-component analysis or other fusion techniques to generate a fused condition indicator that incorporates information from more than one condition indicator.



The Working Principle of RUL Estimator Models: The Similarity Model



Similarity models are useful when you have run-to-failure data (the complete histories from a fleet with the same type of engine, from healthy state through to degradation and failure).

The Working Principle of RUL Estimator Models: The Similarity Model in MATLAB

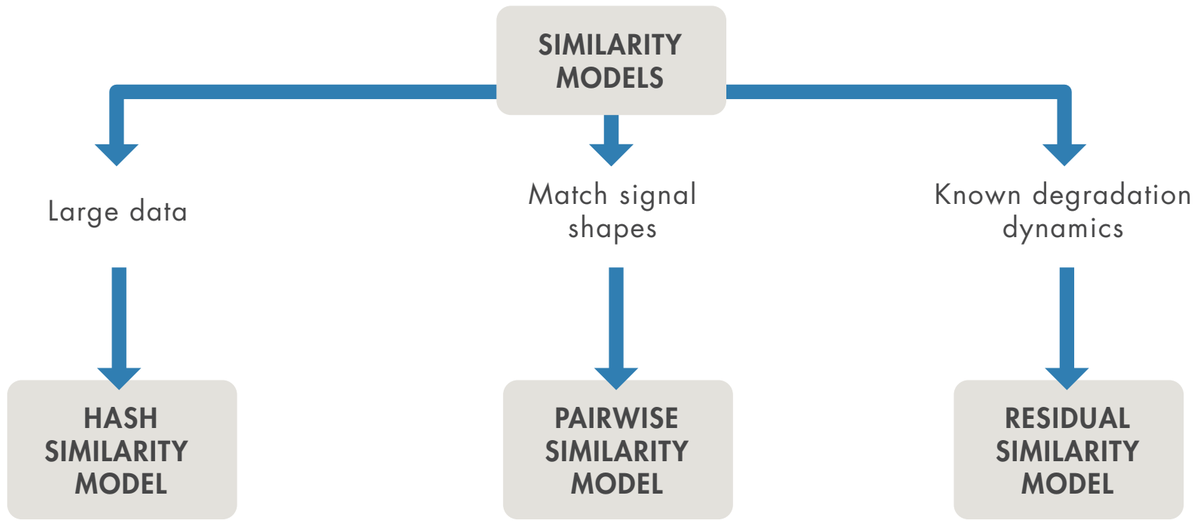
Predictive Maintenance Toolbox includes three types of similarity models:

Hashed-feature similarity model (`hashSimilarityModel`) transforms historical degradation data from each member of your ensemble into fixed-size, condensed information such as the mean, maximum, or minimum values, etc.

Pairwise similarity model (`pairwiseSimilarityModel`) finds the components whose historical degradation paths are most correlated to those of the test component.

Residual similarity model (`residualSimilarityModel`) fits prior data to a model such as an ARMA model or a model that is linear or exponential in usage time. It then computes the residuals between the data predicted from the ensemble models and the data from the test component. See *Similarity-Based Remaining Useful Life Estimation* for more information.

The following section discusses the similarity model in more detail to illustrate how an RUL prediction is performed.



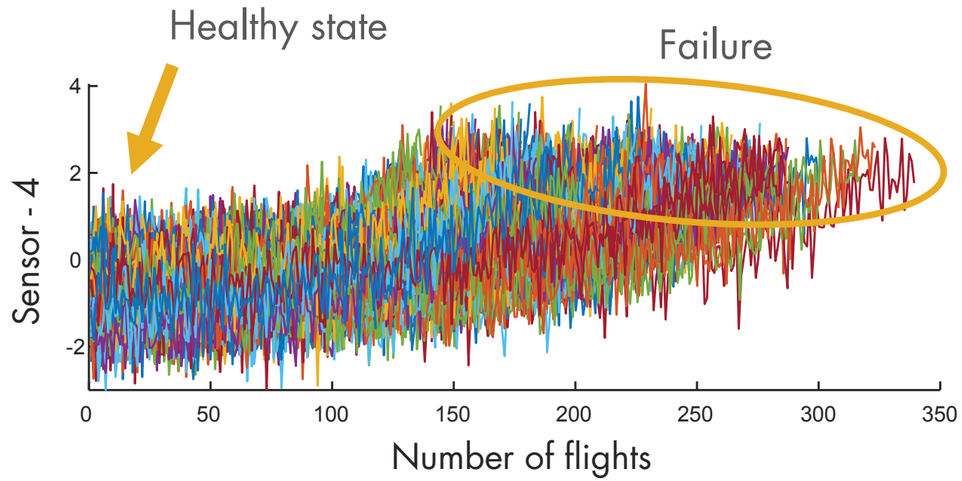
RUL Estimation Workflow Using the Similarity Model

Acquiring Data

The similarity model is a useful RUL estimation technique. See how this model is used in an example to better understand how an RUL prediction is performed.

The first step when developing a predictive maintenance model is to acquire data. This example uses the Prognostics and Health Management challenge dataset publicly available on *NASA's data repository*. This data set includes run-to-failure data from 218 engines, where each engine dataset contains measurements from 21 sensors. Measurements such as fuel flow, temperature, and pressure are gathered through sensors placed in various locations in the engine to provide measurements to the control system and monitor the engine's health. The plot shows what one sensor's measurements look like for all 218 engines.

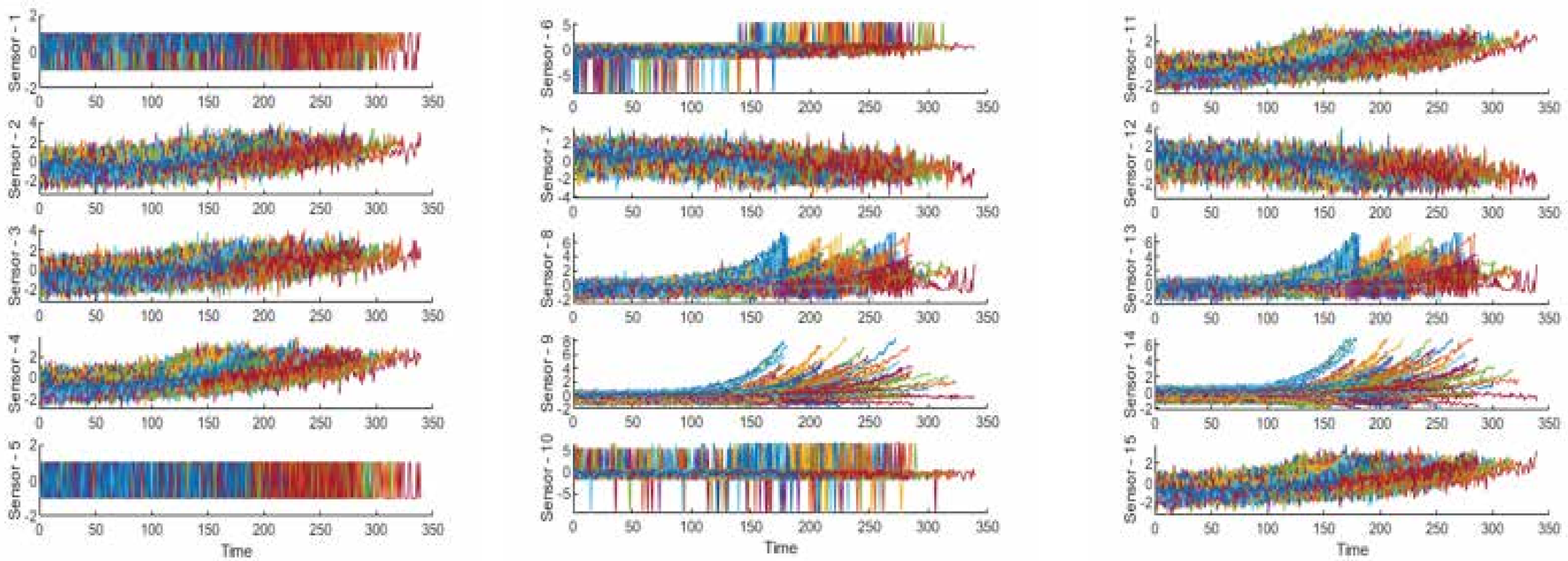
On the plot, the x-axis shows the number of cycles (flights), and the y-values represent the averaged sensor values at each flight. Each engine starts in a healthy state and ends in failure.



RUL Estimation Workflow Using the Similarity Model *continued*

Preprocessing Data and Identifying Condition Indicators

The previous page showed data from Sensor 4, but the full dataset also includes data from 20 other sensors. If you take a closer look at some of the other sensor readings, you can see that some of these measurements don't show a significant trend toward failure (such as Sensors 1, 5, 6, and 10). Therefore, they won't contribute to the selection of useful features for training a similarity model.



RUL Estimation Workflow Using the Similarity Model *continued*

Preprocessing Data and Identifying Condition Indicators

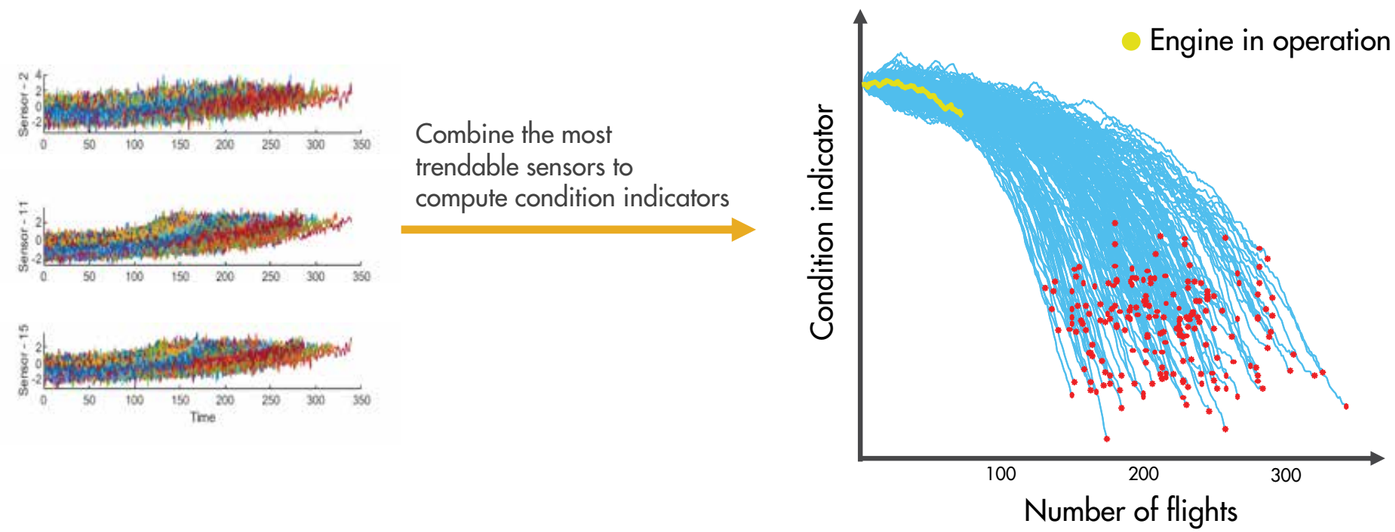
Instead of using all the sensor measurements, identify the three most trendable datasets (the ones that show a significant change in their profile between the healthy state and failure). Sensors 2, 11, and 15 are good candidates to use together to create degradation profiles.

Degradation profiles represent the evolution of one or more condition indicators for each machine in the ensemble (each component), as the machine transitions from a healthy state to a faulty state.

In the preprocessing step, data reduction is performed by selecting only the most trendable sensors (Sensor 2, 11, and 15) and combining them to compute condition indicators.

For more information on how to select and employ condition indicators, see *Predictive Maintenance: Extracting Condition Indicators with MATLAB.*

To estimate the remaining useful life for the current engine (shown in yellow), you would use Sensors 2, 11, and 15 to compute condition indicators that represent the degradation profiles of the fleet. In the graph on the right, you can see that the engine is currently at 60 flights, and the red dots mark where similar engines in the fleet have failed.



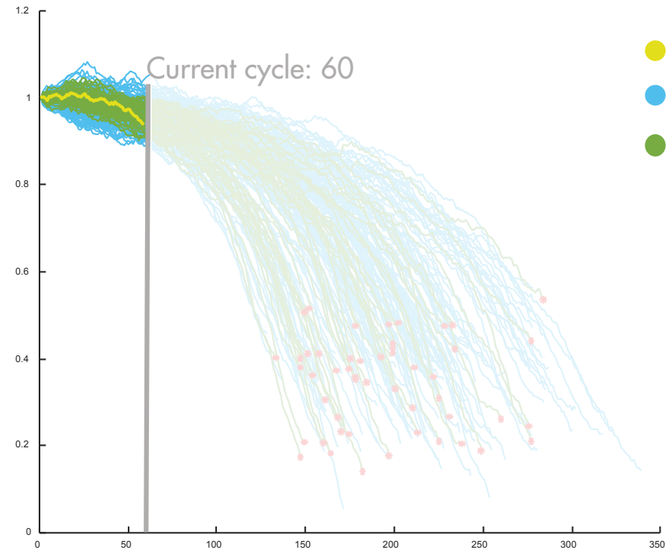
RUL Estimation Workflow Using the Similarity Model *continued*

Training a Similarity Model

You'll want to split the data into two groups, using a larger portion of it to train a similarity model and the rest to test the trained model. You use the known RUL to evaluate the trained model's accuracy.

The similarity model works by finding the closest engine profiles to your engine up to the current cycle. You have the failure times of the closest engines from the historical fleet data, which gives you an idea of the expected failure time of your current engine. You can use this data to fit a probability distribution as seen in the bottom plot.

The median of this distribution gives you the remaining useful life estimate of your engine, which you can compare to the actual RUL to measure accuracy.

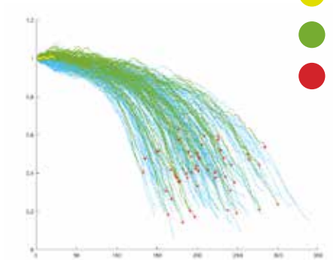


RUL Estimation Workflow Using the Similarity Model *continued*

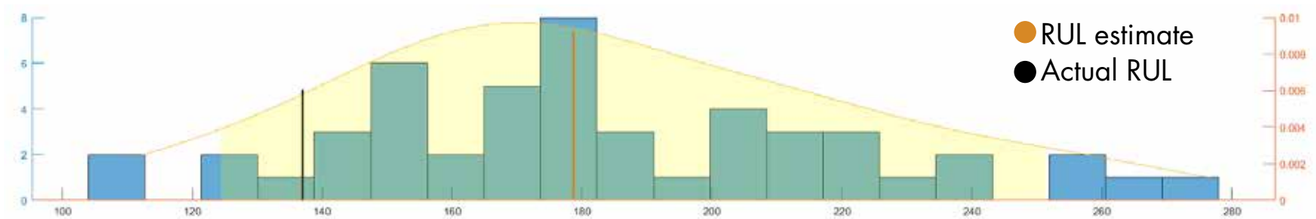
Training a Similarity Model

At each iteration of the RUL computation, the similarity model finds the closest engine paths, which are shown in green, and computes the RUL using a probability distribution plot (shown on the right). The plots below show the engine profiles and their probability distribution for three cycles: 25, 65, and 115.

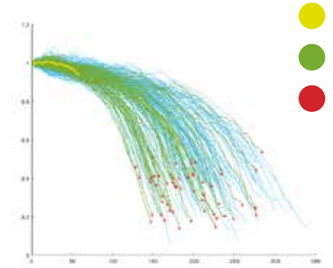
Current Cycle 25



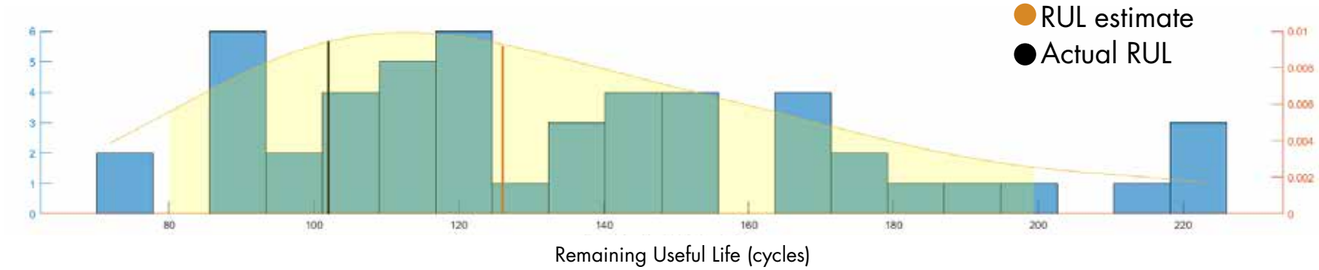
Engine in operation
Closest 50 profiles
Failure times



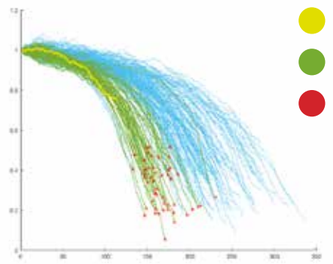
Current Cycle 65



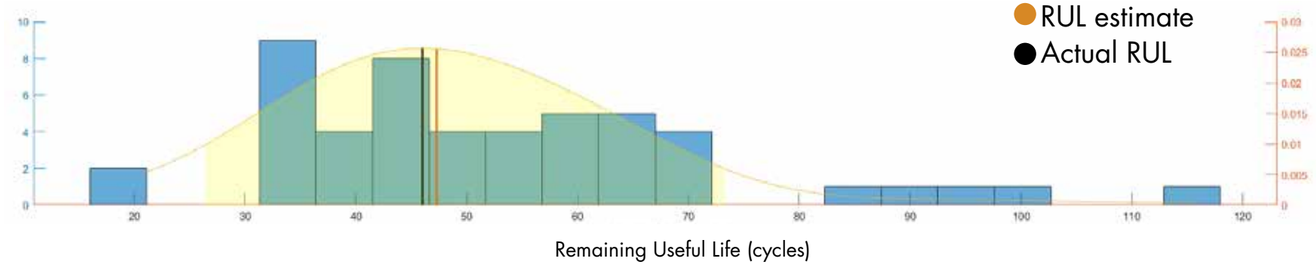
Engine in operation
Closest 50 profiles
Failure times



Current Cycle 115



Engine in operation
Closest 50 profiles
Failure times



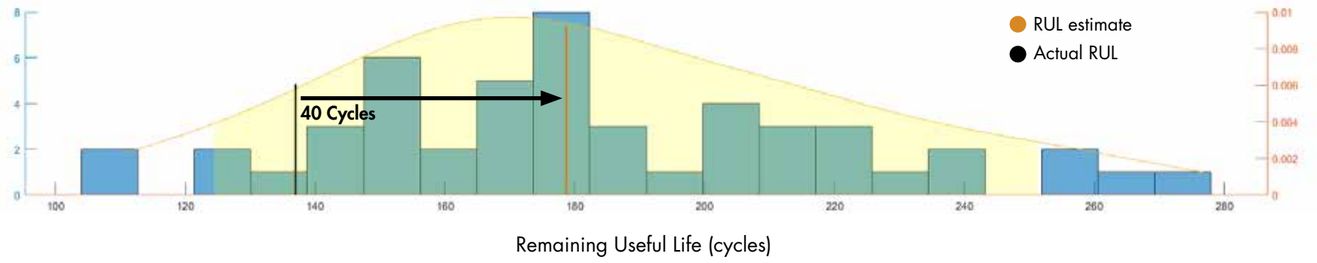
RUL Estimation Workflow Using the Similarity Model *continued*

Training a Similarity Model

On the probability distribution plots, the orange lines represent the predicted RULs and the black lines show the actual RUL.

Notice that the predicted RUL gets closer to the actual RUL as time passes and the model has more data.

Current Cycle 25

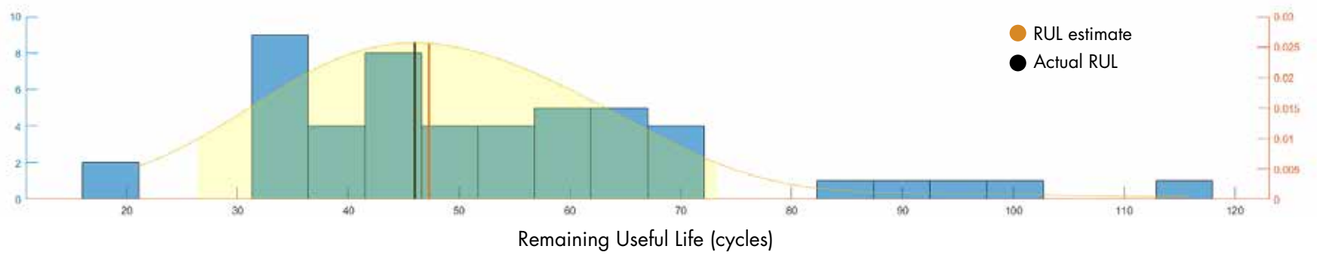


When the engine is at 25 cycles (or flights), the model doesn't have much data to work with yet, so the prediction is 40 cycles off from the true value with a very wide distribution.

As the model gets new data from the engine, the similarity model trains on a larger set of data, as seen at cycle 65 and 115. As a result, the prediction accuracy improves over time.

With more data the RUL predictions become more accurate and the distribution more concentrated.

Current Cycle 115



Using the RUL estimation from cycle 115, you would have a reasonably accurate expectation of your engine's RUL and be able to schedule maintenance at the best time.

Learn More

Ready for a deeper dive? Explore these resources to learn more about predictive maintenance workflow, examples, and tools.

Watch

What Is Predictive Maintenance Toolbox? (2:06) - Video
Predictive Maintenance Tech Talks - Video Series
Predictive Maintenance in MATLAB and Simulink (35:54) - Video
Feature Extraction Using Diagnostic Feature Designer App (4:45) - Video

Read

Overcoming Four Common Obstacles to Predictive Maintenance - White Paper
MATLAB and Simulink for Predictive Maintenance - Overview
MATLAB Predictive Maintenance Examples - Code Examples

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