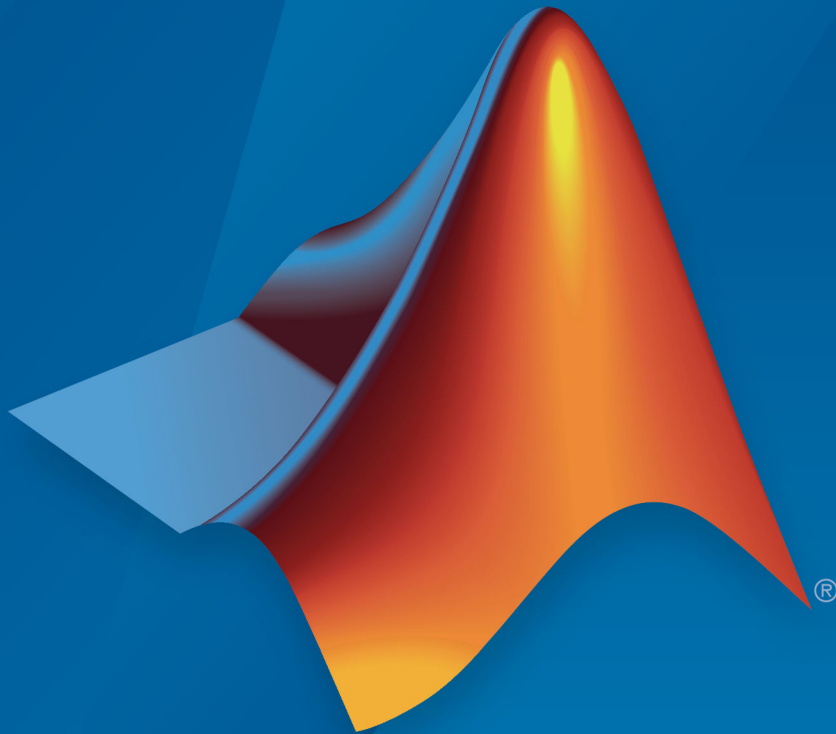


# Predictive Maintenance Toolbox™

Reference



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R2018b

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## *Predictive Maintenance Toolbox™ Reference*

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## **Revision History**

March 2018	Online only	New for Version 1.0 (Release 2018a)
September 2018	Online only	Revised for Version 1.1 (Release 2018b)

**1** | Functions – Alphabetical List

**2** | Objects – Alphabetical List



# Functions — Alphabetical List

---

## approximateEntropy

Measure of regularity of nonlinear time series

### Syntax

```
approxEnt = approximateEntropy(X)  
approxEnt = approximateEntropy( ___, Name, Value)
```

### Description

`approxEnt = approximateEntropy(X)` estimates the approximate entropy of the uniformly sampled time-domain signal `X` by reconstructing the phase space. Approximate entropy is a measure to quantify the amount of regularity and unpredictability of fluctuations over a time series.

`approxEnt = approximateEntropy( ___, Name, Value)` estimates the approximate entropy with additional options specified by one or more `Name, Value` pair arguments.

### Examples

#### Compute Approximate Entropy of Signals

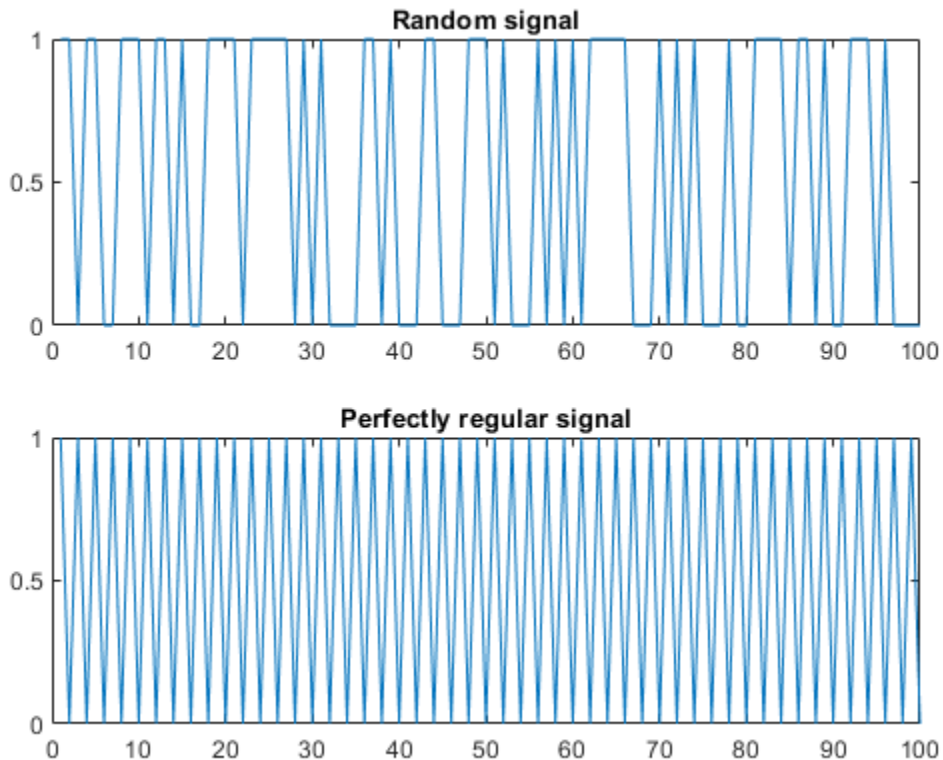
For this example, generate two signals for comparison — a random signal `xRand` and a perfectly regular signal `xReg`. Set `rng` to `default` for reproducibility of the random signal.

```
rng('default');  
xRand = double(randn(100,1)>0);  
xReg = repmat([1;0],50,1);
```

Visualize the random and regular signals.

```
figure;  
subplot(2,1,1);
```

```
plot(xRand);  
title('Random signal');  
subplot(2,1,2);  
plot(xReg);  
title('Perfectly regular signal');
```



The plots show that the regular signal is more predictable than the random signal.

Find approximate entropy of the two signals.

```
valueReg = approximateEntropy(xReg)
```

```
valueReg = 2.6141e-04
```

```
valueIrreg = approximateEntropy(xRand)
```

```
valueIrreg = 0.7289
```

The approximate entropy of the perfectly regular signal is significantly smaller than the random signal. Hence, the perfectly regular signal containing many repetitive patterns has a relatively small value of approximate entropy while the less predictable random signal has a higher value of approximate entropy.

## Input Arguments

### **X — Uniformly sampled time-domain signal**

vector | array | timetable

Uniformly sampled time-domain signal, specified as either a vector, array, or timetable. If X has multiple columns, `approximateEntropy` computes the approximate entropy by treating X as a multivariate signal.

If X is specified as a row vector, `approximateEntropy` treats it as a univariate signal.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `..., 'Dimension', 3`

### **Dimension — Embedding dimension**

2 (default) | scalar | vector

Embedding dimension, specified as the comma-separated pair consisting of `'Dimension'` and a scalar or vector. When `Dimension` is scalar, every column in X is reconstructed using `Dimension`. When `Dimension` is a vector having same length as the number of columns in X, the reconstruction dimension for column `i` is `Dimension(i)`.

Specify `Dimension` based on the dimension of your system. For more information on embedding dimension, see `phaseSpaceReconstruction`.

### **Lag — Delay in phase space reconstruction**

1 (default) | scalar | vector



Delay in phase space reconstruction, specified as the comma-separated pair consisting of 'Lag' and a scalar. When Lag is scalar, every column in X is reconstructed using Lag. When Lag is a vector having same length as the number of columns in X, the reconstruction delay for column i is Lag(i).

If the delay is too small, random noise is introduced in the data. In contrast, if the lag is too large, the reconstructed dynamics does not represent the true dynamics of the time series. For more information on calculating optimal delay, see `phaseSpaceReconstruction`.

### Radius — Similarity criterion

$0.2 * \text{variance}(X) \mid 0.2 * \sqrt{\text{trace}(\text{cov}(X))} \mid \text{scalar}$

Similarity criterion, specified as the comma-separated pair consisting of 'Radius' and a scalar. The similarity criterion, also called radius of similarity, is a tuning parameter that is used to identify a meaningful range in which fluctuations in data are to be considered similar.

The default value of Radius is,

- $0.2 * \text{variance}(X)$ , if X has a single column.
- $0.2 * \sqrt{\text{trace}(\text{cov}(X))}$ , if X has multiple columns.

## Output Arguments

### approxEnt — Approximate entropy of nonlinear time series

scalar

Approximate entropy of nonlinear times series, returned as a scalar. Approximate entropy is a regularity statistic that quantifies the unpredictability of fluctuations in a time series. A relatively higher value of approximate entropy reflects the likelihood that similar patterns of observations are not followed by additional similar observations.

For example, consider two binary signals S1 and S2,

S1 = [0 1 0 1 0 1 0 1 0 1 0 1 0 1];

S2 = [1 1 0 1 1 1 1 0 1 0 1 0 0 0 1];

Signal S1 is perfectly regular since it alternates between 0 and 1, that is, you can predict the next value with knowledge of the previous value. Signal S2 however offers no insight

into the next value, even with prior knowledge of the previous value. Hence, signal S2 is random and less predictable. Therefore, a signal containing highly repetitive patterns has a relatively small value of `approxEnt` while a less predictable signal has a relatively larger value of `approxEnt`.

Use `approximateEntropy` as a measure of regularity to quantify levels of complexity within a time series. The ability to discern levels of complexity within data sets is useful in the field of engineering to estimate component failure by studying their vibration and acoustic signals, or in the clinical domain where, for instance, the chance of a seizure is predicted by observing Electroencephalography (EEG) patterns.[2][3]

## Algorithms

Approximate entropy is computed in the following way,

- 1 The `approximateEntropy` function first generates a delayed reconstruction  $Y_{1:N}$  for  $N$  data points with embedding dimension  $m$ , and lag  $\tau$ .
- 2 The software then calculates the number of within range points, at point  $i$ , given by,

$$N_i = \sum_{k=1, k \neq i}^N \mathbf{1}(\|Y_i - Y_k\|_\infty < R)$$

where  $\mathbf{1}$  is the indicator function, and  $R$  is the radius of similarity.

- 3 The approximate entropy is then calculated as  $\text{approxEnt} = \Phi_m - \Phi_{m+1}$  where,

$$\Phi_m = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log(N_i)$$

## References

- [1] Pincus, Steven M. "Approximate entropy as a measure of system complexity." *Proceedings of the National Academy of Sciences*. 1991 88 (6) 2297-2301; doi: 10.1073/pnas.88.6.2297.
- [2] U. Rajendra Acharya, Filippo Molinari, S. Vinitha Sree, Subhagata Chattopadhyay, Kwan-Hoong Ng, Jasjit S. Suri. "Automated diagnosis of epileptic EEG using

entropies." *Biomedical Signal Processing and Control* Volume 7, Issue 4, 2012, Pages 401-408, ISSN 1746-8094.

- [3] Caesarendra, Wahyu & Kosasih, P & Tieu, Kiet & Moodie, Craig. "An application of nonlinear feature extraction-A case study for low speed slewing bearing condition monitoring and prognosis." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics: Mechatronics for Human Wellbeing, AIM 2013*.1713-1718. 10.1109/AIM.2013.6584344.
- [4] Kantz, H., and Schreiber, T. *Nonlinear Time Series Analysis*. Cambridge: Cambridge University Press, 2003.

## See Also

correlationDimension | lyapunovExponent | phaseSpaceReconstruction

**Introduced in R2018a**

## compare

Compare test data to historical data ensemble for similarity models

### Syntax

```
compare mdl, data)
compare( ____, Name, Value)
```

### Description

`compare(mdl, data)` plots the test component degradation data in `data` superimposed on the most similar data sets from the historical ensemble stored in the fitted similarity model `mdl`. The  $K$  most similar data sets from the ensemble are plotted, where  $K$  is the `NumNearestNeighbors` property of `mdl`.

`compare( ____, Name, Value)` specifies plotting options using one or more name-value pair arguments.

### Examples

#### Compare Test Data to Historical Data

Load training data.

```
load('pairwiseTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component.

Create and train a pairwise similarity model.

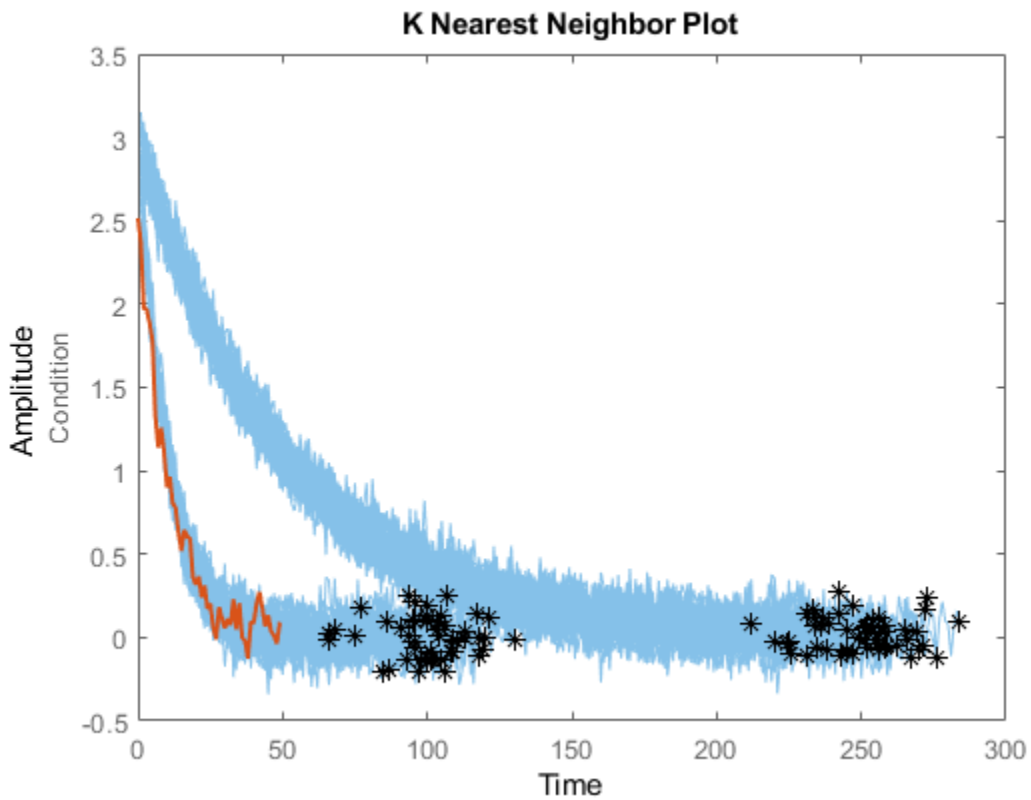
```
mdl = pairwiseSimilarityModel;
fit(mdl, pairwiseTrainTables, "Time", "Condition")
```

Load testing data.

```
load('pairwiseTestData.mat')
```

Compare the degradation profile of the test data to the profiles of the historical data ensemble.

```
compare mdl, pairwiseTestData)
```



### Compare Test Data to Most Similar Historical Data

Load training data.

```
load('pairwiseTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component.

Create and train a pairwise similarity model.

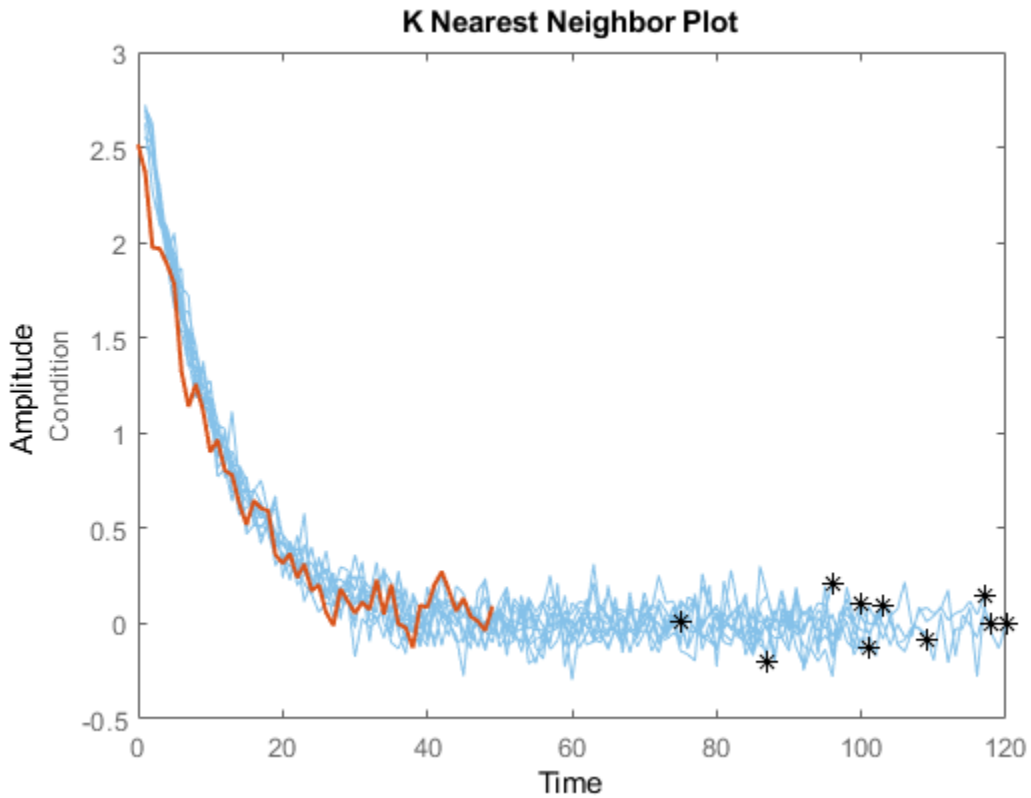
```
mdl = pairwiseSimilarityModel;  
fit(mdl, pairwiseTrainTables, "Time", "Condition")
```

Load testing data.

```
load('pairwiseTestData.mat')
```

Compare the degradation profile of the test data to the profiles of the 10 most similar members of the historical data ensemble.

```
compare(mdl, pairwiseTestData, 'NumNearestNeighbors', 10)
```



## Input Arguments

### **mdl** — Similarity RUL model

`hashSimilarityModel object` | `pairwiseSimilarityModel object` |  
`residualSimilarityModel object`

Similarity RUL model, specified as a `hashSimilarityModel` object, a `pairwiseSimilarityModel` object, or a `residualSimilarityModel` object. The model must be fitted using `fit` before calling `compare`.

## **data — Degradation feature measurements**

array | table | timetable

Degradation feature profiles for estimating the RUL of similarity models, measured over the life span of a component up to the current life time, specified as one of the following:

- $(N+1)$ -by- $M$  numeric array, where  $N$  is the number of features and  $M$  is the number of feature measurements. In each row, the first column contains the usage time and the remaining columns contain the corresponding degradation feature measurements. The order of the features must match the order specified in the `DataVariables` property of `mdl`.
- `table` or `timetable` object — The table must contain variables with names that match the strings in the `DataVariables` and `LifeTimeVariable` properties of `mdl`.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `'NumNearestNeighbors', '10'` plots ten similar data sets

## **NumNearestNeighbors — Number of nearest neighbors**

`Inf` | finite positive integer

Number of nearest neighbors, specified as the comma-separated pair `'NumNearestNeighbors'` and either `Inf` or a finite positive integer. Use this option to select the number of most similar data sets to plot by overriding the `NumNearestNeighbors` property. If `NumNearestNeighbors` is `Inf`, then compare plots the degradation data for all the ensemble data sets.

## **Threshold — Degradation data bounds**

two-column array

Degradation data bounds, specified as the comma-separated pair `'Threshold'` and a two-column array with  $N$  rows, where  $N$  is the number of data variables used by `mdl`. The first column of `Threshold` contains the lower bounds for the variables, and the second column contains the upper bounds. The bounds are rendered as yellow-colored patches.

To disable the bounds for a given variable, specify the lower and upper bounds as `-Inf` and `Inf`, respectively.



## Tips

- To select which signals to plot, right-click on the plot area, and select **Data Variable Selector**. In the Data Variable Selector dialog box, the **Select Variables** box shows the variables that are available for plotting.

## See Also

### Functions

`hashSimilarityModel` | `pairwiseSimilarityModel` | `residualSimilarityModel`

**Introduced in R2018a**

## correlationDimension

Measure of chaotic signal complexity

### Syntax

```
corDim = correlationDimension(X)
[corDim,rRange,corInt] = correlationDimension(X)
___ = correlationDimension(___ ,Name,Value)

correlationDimension(X)
```

### Description

`corDim = correlationDimension(X)` estimates the correlation dimension of the uniformly sampled time-domain signal `X`. Correlation dimension is the measure of dimensionality of the space occupied by a set of random points. `corDim` is estimated as the slope of the correlation integral versus the range of radius of similarity. Use `correlationDimension` as a characteristic measure to distinguish between deterministic chaos and random noise, to detect potential faults.[1]

`[corDim,rRange,corInt] = correlationDimension(X)` additionally estimates the range of radius of similarity and correlation integral of the uniformly sampled time-domain signal `X`. Correlation integral is the mean probability that the states of a system are close at two different time intervals, which reflects self-similarity.

`___ = correlationDimension(___ ,Name,Value)` estimates the correlation dimension with additional options specified by one or more `Name,Value` pair arguments.

`correlationDimension(X)` with no output arguments creates a correlation integral versus neighborhood radius plot.

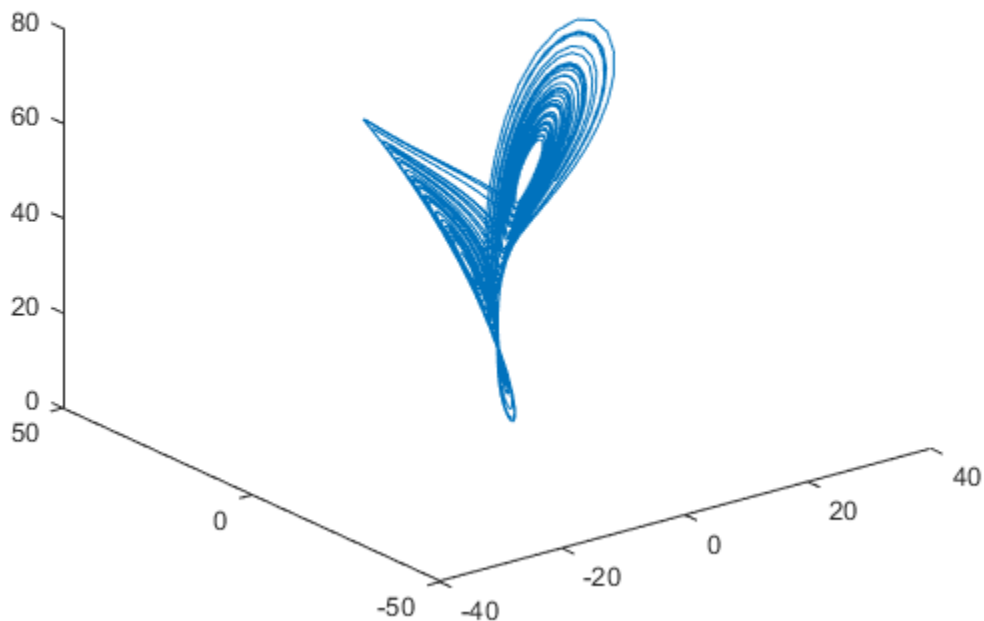
### Examples

## Visualize and Estimate Correlation Dimension of Data

In this example, consider a Lorenz Attractor describing a unique set of chaotic solutions.

Load the data set and visualize the Lorenz Attractor in 3D.

```
load('lorenzAttractorExampleData.mat','data');  
plot3(data(:,1),data(:,2),data(:,3));
```



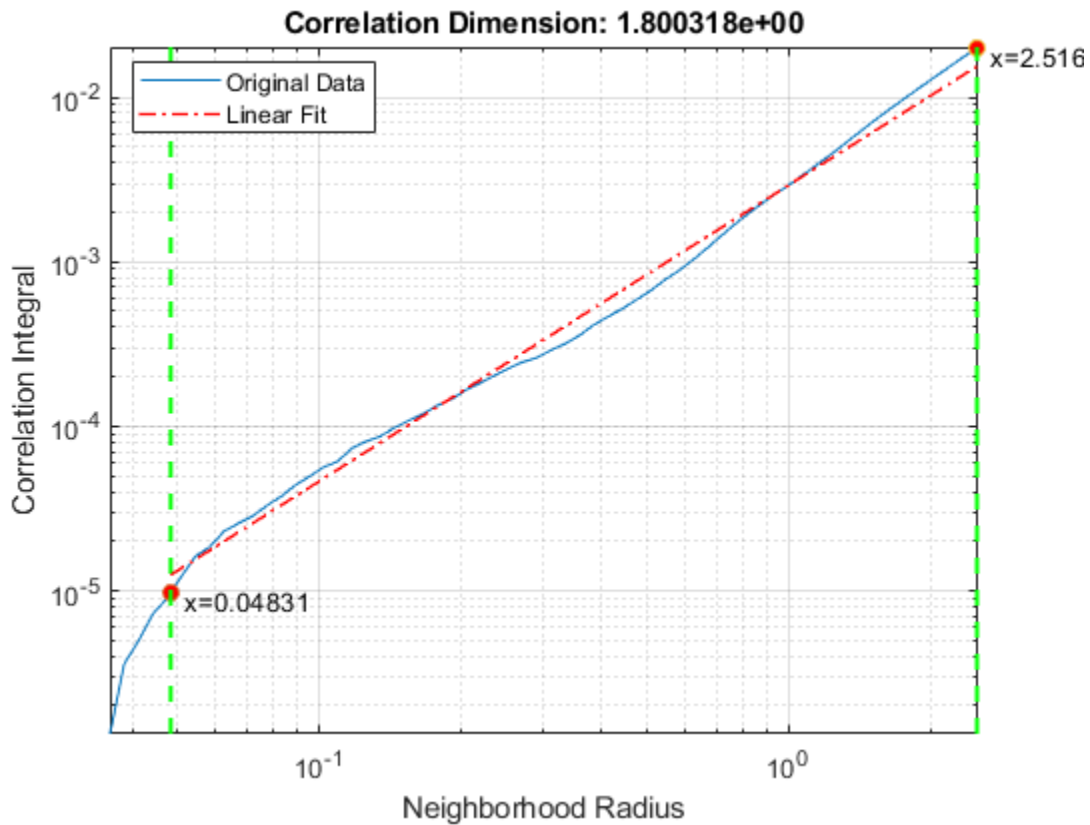
For this example, use only x-direction data of the Lorenz Attractor. Since Lag is unknown, estimate the delay using `phaseSpaceReconstruction`. Set 'Dimension' to 3 since the Lorenz Attractor is a three-dimensional system. The Dimension and Lag parameters are required to create the correlation integral versus the neighborhood radius plot.

```
xdata = data(:,1);
dim = 3;
[~,lag] = phaseSpaceReconstruction(xdata,[],dim)

lag = 10
```

Create the correlation integral versus neighborhood radius plot for the Lorenz Attractor, using the Lag value obtained in the previous step. Set an appropriate value for 'NumPoints' to determine a good resolution for the neighborhood radius.

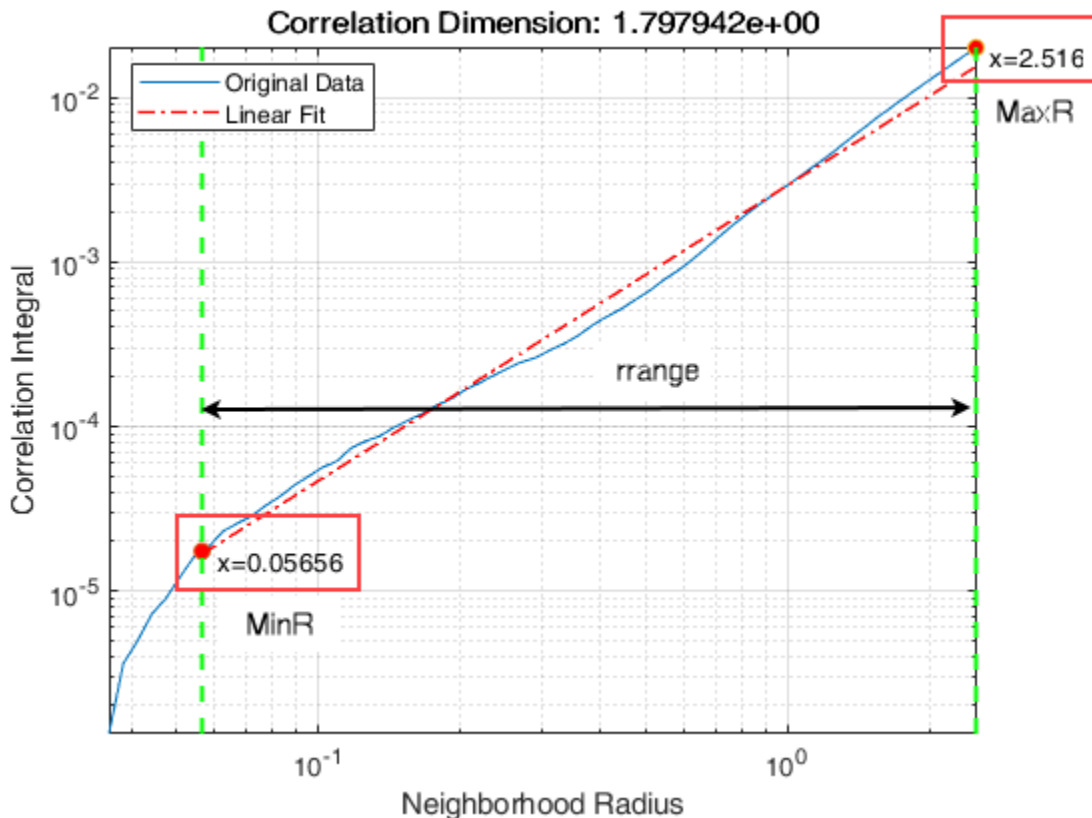
```
Np = 100;
correlationDimension(xdata, 'Dimension',dim, 'Lag',lag, 'NumPoints',Np);
```



The first dashed, vertical green line (on the left) indicates the value of  $\text{MinRadius}$ , while the second vertical green line (on the right), represents  $\text{MaxRadius}$ . The dashed red line indicates the linear fit line for the correlation integral versus neighborhood radius data, within the computed range of radius.

To compute correlation dimension, you first need to determine the  $\text{MinRadius}$  and  $\text{MaxRadius}$  values needed for accurate estimation.

In the plot, drag the two dashed, vertical green lines to 'best fit' the linear fit line to the original data line to obtain the range of radius.



Note the new values of  $\text{MinRadius}$  and  $\text{MaxRadius}$  after dragging the two vertical lines for an appropriate fit.

Find the correlation dimension of the Lorenz Attractor, using the new `MinRadius` and `MaxRadius` values obtained in the previous step.

```
MinR = 0.05656;  
MaxR = 2.516;  
corDim = correlationDimension(xdata, 'Dimension', dim, 'MinRadius', MinR, 'MaxRadius', MaxR,  
corDim = 1.7490
```

The value of correlation dimension is directly proportional to the level of chaos in the system, that is, a higher value of `corDim` represents a high level of chaotic complexity in the system.

## Input Arguments

### **X** — Uniformly sampled time-domain signal

vector | array | timetable

Uniformly sampled time-domain signal, specified as a vector, array, or timetable. If `X` has multiple columns, `correlationDimension` computes the correlation dimension by treating `X` as a multivariate signal.

If `X` is specified as a row vector, `correlationDimension` treats it as a univariate signal.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `..., 'Dimension', 3`

### **Dimension** — Embedding dimension

2 (default) | scalar | vector

Embedding dimension, specified as the comma-separated pair consisting of `'Dimension'` and a scalar or vector. When `Dimension` is scalar, every column in `X` is reconstructed using `Dimension`. When `Dimension` is a vector having same length as the number of columns in `X`, the reconstruction dimension for column `i` is `Dimension(i)`.

Specify `Dimension` based on the dimension of your system, that is, the number of states. For more information on embedding dimension, see `phaseSpaceReconstruction`.

**Lag — Delay in phase space reconstruction**

1 (default) | scalar | vector

Delay in phase space reconstruction, specified as the comma-separated pair consisting of 'Lag' and either a scalar or vector. When `Lag` is scalar, every column in `X` is reconstructed using `Lag`. When `Lag` is a vector having same length as the number of columns in `X`, the reconstruction delay for column `i` is `Lag(i)`.

If the delay is too small, random noise is introduced in the data. In contrast, if the lag is too large, the reconstructed dynamics does not represent the true dynamics of the time series. For more information on estimating optimal delay, see `phaseSpaceReconstruction`.

**MinRadius — Minimum radius of similarity**

MaxRadius/1000 (default) | scalar

Minimum radius of similarity, specified as the comma-separated pair consisting of 'MinRadius' and a scalar. Find the optimal value of `MinRadius` by adjusting the linear fit of the correlation dimension plot.

**MaxRadius — Maximum radius of similarity**

0.2\*sqrt(trace(cov(X))) (default) | scalar

Maximum radius of similarity, specified as the comma-separated pair consisting of 'MaxRadius' and a scalar. Find the optimal value of `MaxRadius` by adjusting the linear fit of the correlation dimension plot.

**NumPoints — Number of points for computation**

10 (default) | positive scalar integer

Number of points for computation, specified as the comma-separated pair consisting of 'NumPoints' and a positive scalar integer. `NumPoints` is the number of points between `MinRadius` and `MaxRadius`. Choose an appropriate value for `NumPoints` based on the resolution required for `rRange`.

`NumPoints` only accepts values greater than 1, and the default value is 10.

## Output Arguments

### **corDim** — Correlation Dimension

scalar

Correlation dimension, returned as a scalar. `corDim` is a measure of chaotic signal complexity in multidimensional phase space and is the slope of the correlation integral versus the range of radius of similarity. `corDim` is used in fault detection as a characteristic measure to distinguish between deterministic chaos and random noise.

### **rRange** — Range of radius of similarity

array

Radius of similarity, returned as an array. `rRange` is the difference between `MaxRadius` and `MinRadius` split into an equal number of points defined by `NumPoints`.

### **corInt** — Correlation integral

array

Correlation integral, returned as an array. `corInt` is the mean probability that the states at two different times are close, which reflects self-similarity. `NumPoints` defines the length of `corInt` array.

## Algorithms

Correlation dimension is computed in the following way,

- 1 The `correlationDimension` function first generates a delayed reconstruction  $Y_{1:N}$  with embedding dimension  $m$ , and lag  $\tau$ .
- 2 The software then calculates the number of with-in range points, at point  $i$ , given by,

$$N_i(R) = \sum_{i=1, i \neq k}^N \mathbf{1}(\|Y_i - Y_k\| < R)$$

where  $\mathbf{1}$  is the indicator function, and  $R$  is the radius of similarity, given by,  $R = \exp(\text{linspace}(\log(r_{min}), \log(r_{max}), N))$ . Here,  $r_{min}$  is `MinRadius`,  $r_{max}$  is `MaxRadius`, and  $N$  is `NumPoints`.

- 3 The correlation dimension `corDim` is the slope of  $C(R)$  vs.  $R$  where, the correlation integral  $C(R)$  is defined as,



$$C(R) = \frac{2}{N(N-1)} \sum_{i=1}^N N_i(R)$$

## References

- [1] Caesarendra, Wahyu & Kosasih, P & Tieu, Kiet & Moodie, Craig. "An application of nonlinear feature extraction-A case study for low speed slewing bearing condition monitoring and prognosis." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics: Mechatronics for Human Wellbeing, AIM 2013*.1713-1718. 10.1109/AIM.2013.6584344.
- [2] Theiler, James. "Efficient algorithm for estimating the correlation dimension from a set of discrete points". American Physical Society. *Physical Review A* 1987/11/1. Volume 36. Issue 9. Pages 44-56.

## See Also

[approximateEntropy](#) | [lyapunovExponent](#) | [phaseSpaceReconstruction](#)

**Introduced in R2018a**

## fit

Estimate parameters of remaining useful life model using historical data

The `fit` function estimates the parameters of a remaining useful life (RUL) prediction model using historical data regarding the health of an ensemble of similar components, such as multiple machines manufactured to the same specifications. Depending on the type of model, you specify the historical health data as a collection of lifespan measurements or degradation profiles. Once you estimate the parameters of your model, you can then predict the remaining useful life of similar components using the `predictRUL` function.

Using `fit`, you can configure the parameters for the following types of estimation models:

- Degradation models
- Survival models
- Similarity models

For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life using these models, see “RUL Estimation Using RUL Estimator Models”.

## Syntax

```
fit mdl, data  
fit mdl, data, lifeTimeVariable  
fit mdl, data, lifeTimeVariable, dataVariables
```

```
fit mdl, data, lifeTimeVariable, dataVariables, censorVariable  
fit mdl, data, lifeTimeVariable, dataVariables, censorVariable,  
encodedVariables
```

## Description

`fit mdl, data` fits the parameters of the remaining useful life model `mdl` using the historical data in `data`. This syntax applies only when `data` does not contain `table` or `timetable` data.

`fit mdl, data, lifeTimeVariable` fits the parameters of `mdl` using the time variable `lifeTimeVariable` and sets the `LifeTimeVariable` property of `mdl`. This syntax applies only when `data` contains:

- Nontabular data
- Tabular data, and `mdl` does not use data variables

`fit mdl, data, lifeTimeVariable, dataVariables` fits the parameters of `mdl` using the data variables in `dataVariables` and sets the `DataVariables` property of `mdl`.

`fit mdl, data, lifeTimeVariable, dataVariables, censorVariable` specifies the censor variable for a survival model and sets the `CensorVariable` property of `mdl`. The censor variable indicates which life-time measurements in `data` are not end-of-life values. This syntax applies only when `mdl` is a survival model and `data` contains tabular data.

`fit mdl, data, lifeTimeVariable, dataVariables, censorVariable, encodedVariables` specifies the encoded variables for a covariate survival model and sets the `EncodedVariables` property of `mdl`. Encoded variables are usually nonnumeric categorical features that `fit` converts to numeric vectors before fitting. This syntax applies only when `mdl` is a `covariateSurvivalModel` object and `data` contains tabular data.

## Examples

### Train Linear Degradation Model

Load training data.

```
load('linTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create a linear degradation model with default settings.

```
mdl = linearDegradationModel;
```

Train the degradation model using the training data.

```
fit(mdl,linTrainVectors)
```

## **Train Reliability Survival Model**

Load training data.

```
load('reliabilityData.mat')
```

This data is a column vector of duration objects representing battery discharge times.

Create a reliability survival model with default settings.

```
mdl = reliabilitySurvivalModel;
```

Train the survival model using the training data.

```
fit(mdl,reliabilityData,"hours")
```

## **Train Hash Similarity Model Using Tabular Data**

Load training data.

```
load('hashTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a hash similarity model that uses the following values as hashed features:

```
mdl = hashSimilarityModel('Method',@(x) [mean(x),std(x),kurtosis(x),median(x)]);
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit mdl, hashTrainTables, "Time", "Condition")
```

## Predict RUL Using Covariate Survival Model

Load training data.

```
load('covariateData.mat')
```

This data contains battery discharge times and related covariate information. The covariate variables are:

- Temperature
- Load
- Manufacturer

The manufacturer information is a categorical variable that must be encoded.

Create a covariate survival model, and train it using the training data.

```
mdl = covariateSurvivalModel('LifeTimeVariable', "DischargeTime", 'LifeTimeUnit', "hours",  
    'DataVariables', ["Temperature", "Load", "Manufacturer"], 'EncodedVariables', "Manufacturer")  
fit(mdl, covariateData)
```

Successful convergence: Norm of gradient less than OPTIONS.TolFun

Suppose you have a battery pack manufactured by maker B that has run for 30 hours. Create a test data table that contains the usage time, DischargeTime, and the measured ambient temperature, TestAmbientTemperature, and current drawn, TestBatteryLoad.

```
TestBatteryLoad = 25;  
TestAmbientTemperature = 60;  
DischargeTime = hours(30);  
TestData = timetable(TestBatteryLoad, TestAmbientTemperature, 'B', 'RowTimes', hours(30));  
TestData.Properties.VariableNames = {'Temperature', 'Load', 'Manufacturer'};  
TestData.Properties.DimensionNames{1} = 'DischargeTime';
```

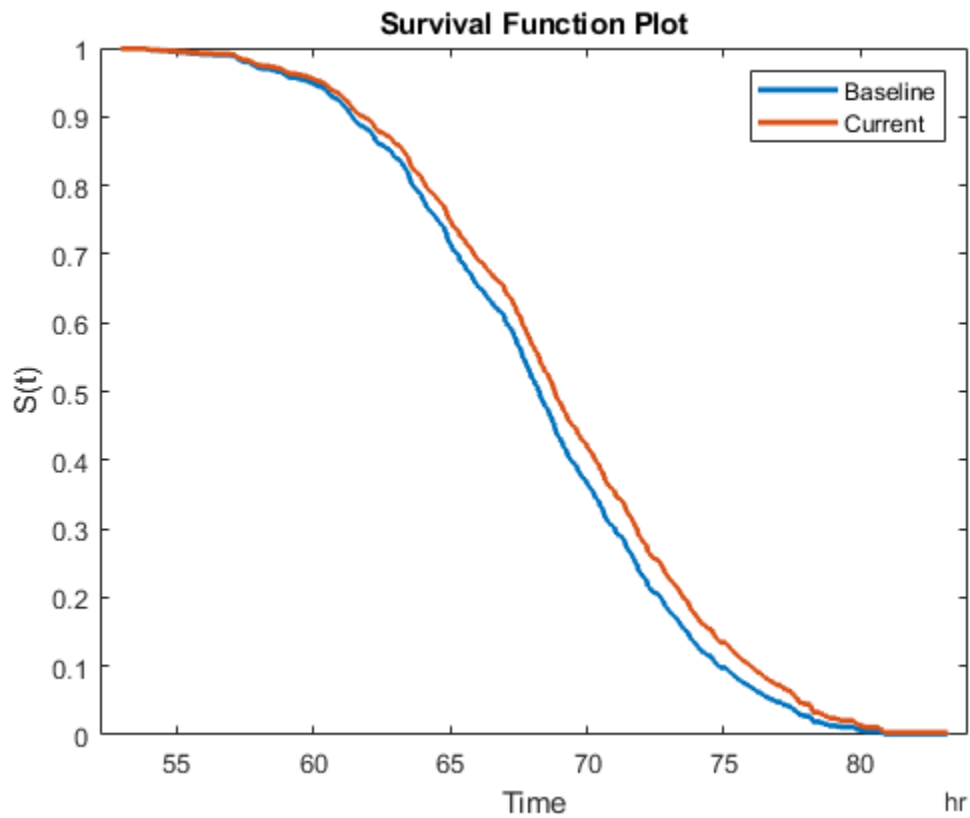
Predict the RUL for the battery.

```
estRUL = predictRUL mdl, TestData)
```

```
estRUL = duration  
38.657 hr
```

Plot the survivor function for the covariate data of the battery.

```
plot(mdl, TestData)
```



## Input Arguments

### **mdl** — Remaining useful life prediction model

degradation model | survival model | similarity model

Remaining useful life prediction model, specified as one of these models. `fit` updates the parameters of this model using the historical data in `data`.

<b>RUL Model Groups</b>	<b>Prediction Model</b>
Degradation models	<code>linearDegradationModel</code>
	<code>exponentialDegradationModel</code>
Survival models	<code>reliabilitySurvivalModel</code>
	<code>covariateSurvivalModel</code>
Similarity models	<code>hashSimilarityModel</code>
	<code>pairwiseSimilarityModel</code>
	<code>residualSimilarityModel</code>

For more information on the different model types and when to use them, see “Models for Predicting Remaining Useful Life”.

### **data** — Historical data

column vector | array | table | timetable | cell array

Historical data regarding the health of an ensemble of similar components, such as their degradation profiles or life spans, specified as an array or table of component life times, or a cell array of degradation profiles.

If your historical data is stored in an ensemble datastore object, you must first convert it to a `table` before estimating your model parameters. For more information, see “Data Ensembles for Condition Monitoring and Predictive Maintenance”.

The format of `data` depends on the type of RUL model you specify in `mdl`.

### **Degradation Model**

If `mdl` is a `linearDegradationModel` or `exponentialDegradationModel`, specify `data` as a cell array of component degradation profiles. Each element of the cell array contains the degradation feature profile across the lifetime of a single component. There

can be only one degradation feature for your model. You can specify `data` as a cell array of:

- Two-column arrays, where each row contains the usage time in the first column and the corresponding feature measurement in the second column. In this case, the usage time column must contain numeric values; that is, it cannot use, for example, `duration` or `timedate` values.
- `table` objects. Select the variable from the table that contains the feature degradation profile using `dataVariables`, and select the usage time variable, if present, using `lifeTimeVariable`.
- `timetable` objects. Select the variable from the table that contains the feature degradation profile using `dataVariables`, and select the usage time variable using `lifeTimeVariable`.

### Survival Model

For survival models, `data` contains the life span measurements for multiple components. Also, for covariate survival models, `data` contains corresponding time-independent covariates, such as the component provider or working regimes. Specify `data` as one of the following:

- Column vector of life span measurements — This case applies only when `mdl` is a `reliabilitySurvivalModel`.
- Array — The first column contains the life span measurements, and the remaining columns contain the covariate values. This case applies only when `mdl` is a `covariateSurvivalModel`.
- `table` or `timetable` — In this case, select the variable from the table that contains the life span measurements using `lifeTimeVariable`. For covariate survival models, select the covariate variables using `dataVariables`. For reliability survival models, `fit` ignores `dataVariables`.

By default, `fit` assumes that all life span measurements are end-of-life values. To indicate that a life span measurement is not an end-of-life value, use `censoring`. To do so, specify `data` as a `table` or `timetable` that contains a censor variable. The censor variable is a binary variable that is `1` when the corresponding life span measurement is not an end-of-life value. Select the censor variable using `sensorVariable`.

### Similarity Model

If `mdl` is a `hashSimilarityModel`, `pairwiseSimilarityModel`, or `residualSimilarityModel`, specify `data` as a cell array of degradation profiles. Each



element of the cell array contains degradation feature profiles across the lifetime a single component. For similarity models, you can specify multiple degradation features, where each feature is a health indicator for the component. You can specify `data` as a cell array of:

- $(N+1)$ -by- $M_i$  column arrays, where  $N$  is the number of features and  $M_i$  is the number of feature measurements. In each row, the first column contains the usage time and the remaining columns contain the corresponding degradation feature measurements.
- `table` objects. Select the variables from the table that contain the feature degradation profiles using `dataVariables`, and select the corresponding usage time variable, if present, using `lifeTimeVariable`.
- `timetable` objects. Select the variables from the table that contain the feature degradation profiles using `dataVariables`, and select the corresponding usage time variable using `lifeTimeVariable`.

`fit` assumes that all the degradation profiles represent run-to-failure data; that is, the data starts when the component is in a healthy state and end when the component is close to failure or maintenance.

### **lifeTimeVariable — Life time variable**

"" (default) | string

Life time variable, specified as a string. If `data` is a:

- `table`, then `lifeTimeVariable` must match one of the variable names in the table.
- `timetable`, then `lifeTimeVariable` one of the variable names in the table or the dimension name of the time variable, `data.Properties.DimensionNames{1}`.

`table` or `timetable`, then `lifeTimeVariable` must match one of the variable names in the table. If there is no life time variable in the table or if `data` is nontabular, then you can omit `lifeTimeVariable`.

`lifeTimeVariable` must be "" or a valid MATLAB® variable name, and must not match any of the strings in `dataVariables`.

`fit` stores `lifeTimeVariable` in the `LifeTimeVariable` property of the model.

### **dataVariables — Feature data variables**

"" (default) | string | string array

Feature data variables, specified as a string or string array. If `data` is a:

- Degradation model, then `dataVariables` must be a string
- Similarity model or covariate survival model, then `dataVariables` must be a string array
- Reliability survival model, then `fit` ignores `dataVariables`

If `data` is:

- A `table` or `timetable`, then the strings in `dataVariables` must match variable names in the table.
- Nontabular, then `dataVariables` must be "" or contain the same number of strings as there are data columns in `data`. The strings in `dataVariables` must be valid MATLAB variable names.

`fit` stores `dataVariables` in the `DataVariables` property of the model.

### **sensorVariable — Censor variable**

"" (default) | string

Censor variable for survival models, specified as a string. The censor variable is a binary variable that indicates which life time measurements in `data` are not end-of-life values. To use censoring, `data` must be a `table` or `timetable`.

If you specify `sensorVariable`, the string must match one of the variable names in `data` and must not match any of the strings in `dataVariables` or `lifeTimeVariable`.

`fit` stores `sensorVariable` in the `SensorVariable` property of the model.

### **encodedVariables — Encoded variables**

"" (default) | string | string array

Encoded variables for covariate survival models, specified as a string or string array. Encoded variables are usually nonnumeric categorical features that `fit` converts to numeric vectors before fitting. You can also designate logical or numeric values that take values from a small set to be encoded.

The strings in `encodedVariables` must be a subset of the strings in `dataVariables`.

`fit` stores `encodedVariables` in the `EncodedVariables` property of the model.

## See Also

### Functions

`predictRUL` | `table` | `timetable`

### Topics

*"Update RUL Prediction as Data Arrives"*

*"RUL Estimation Using RUL Estimator Models"*

*"Data Ensembles for Condition Monitoring and Predictive Maintenance"*

**Introduced in R2018a**

## generateSimulationEnsemble

Generate ensemble data by running a Simulink model

### Syntax

```
[status,E] = generateSimulationEnsemble(simin)  
[status,E] = generateSimulationEnsemble(simin,location)  
[status,E] = generateSimulationEnsemble(simin,location,Name,Value)
```

### Description

[status,E] = generateSimulationEnsemble(simin) generates data for a simulation ensemble by running the Simulink® model specified by simin. This input argument is a vector of Simulink.SimulationInput objects that also specifies other parameters to change from simulation to simulation to generate the ensemble. The function writes the simulation data log files to the current folder. Each file contains the corresponding Simulink.SimulationInput object and all the variables that the model is configured to log for the simulation. The output arguments indicate whether any simulations generate errors and return any such errors. Use simulationEnsembleDatastore to create an ensemble datastore for interacting with the simulated data.

For general information about data ensembles, see “Data Ensembles for Condition Monitoring and Predictive Maintenance”.

[status,E] = generateSimulationEnsemble(simin,location) also specifies a path to a location at which to store the simulation results.

[status,E] = generateSimulationEnsemble(simin,location,Name,Value) uses additional options specified by one or more Name, Value pair arguments.

### Examples

## Generate Ensemble of Fault Data

Generate a simulation ensemble datastore of data representing a machine operating under fault conditions by simulating a Simulink® model of the machine while varying a fault parameter.

Load the Simulink model. This model is a simplified version of the gear-box model described in “Using Simulink to Generate Fault Data”. For this example, only one fault mode is modeled, a gear-tooth fault.

```
mdl = 'TransmissionCasingSimplified';
open_system(mdl)
```

The gear-tooth fault is modeled as a disturbance in the Gear Tooth fault subsystem. The magnitude of the disturbance is controlled by the model variable ToothFaultGain, where ToothFaultGain = 0 corresponds to no gear-tooth fault (healthy operation). To generate the ensemble of fault data, you use generateSimulationEnsemble to simulate the model at different values of ToothFaultGain, ranging from -2 to zero. This function uses an array of Simulink.SimulationInput objects to configure the Simulink model for each member in the ensemble. Each simulation generates a separate member of the ensemble in its own data file. Create such an array, and use setVariable to assign a tooth-fault gain value for each run.

```
toothFaultValues = -2:0.5:0; % 5 ToothFaultGain values

for ct = numel(toothFaultValues):-1:1
    simin(ct) = Simulink.SimulationInput(mdl);
    simin(ct) = setVariable(simin(ct), 'ToothFaultGain', toothFaultValues(ct));
end
```

For this example, the model is already configured to log certain signal values, Vibration and Tacho (see “Export Signal Data Using Signal Logging” (Simulink)). generateSimulationEnsemble further configures the model to:

- Save logged data to files in the folder you specify.
- Use the timetable format for signal logging.
- Store each Simulink.SimulationInput object in the saved file with the corresponding logged data.

Specify a location for the generated data. For this example, save the data to a folder called Data within your current folder. The indicator status is 1 (true) if all the simulations complete without error.

```
mkdir Data
location = fullfile(pwd, 'Data');
[status,E] = generateSimulationEnsemble(simin,location);

[27-Aug-2018 14:27:56] Running SetupFcn...
[27-Aug-2018 14:27:56] Running simulations...
[27-Aug-2018 14:28:51] Completed 1 of 5 simulation runs
[27-Aug-2018 14:29:01] Completed 2 of 5 simulation runs
[27-Aug-2018 14:29:10] Completed 3 of 5 simulation runs
[27-Aug-2018 14:29:18] Completed 4 of 5 simulation runs
[27-Aug-2018 14:29:28] Completed 5 of 5 simulation runs
```

Inside the `Data` folder, examine one of the files. Each file is a MAT-file containing the following MATLAB® variables:

- `SimulationInput` — The `Simulink.SimulationInput` object that was used to configure the model for generating the data in the file. You can use this to extract information about the conditions (such as faulty or healthy) under which this simulation was run.
- `logout` — A `Dataset` object containing all the data that the Simulink model is configured to log.
- `PMSignalLogName` — The name of the variable that contains the logged data ('`logout`' in this example). The `simulationEnsembleDatastore` command uses this name to parse the data in the file.
- `SimulationMetadata` — Other information about the simulation that generated the data logged in the file.

Now you can create the simulation ensemble datastore using the generated data. The resulting `simulationEnsembleDatastore` object points to the generated data. The object lists the data variables in the ensemble, and by default all the variables are selected for reading. Examine the `DataVariables` and `SelectedVariables` properties of the ensemble to confirm these designations.

```
ensemble = simulationEnsembleDatastore(location)
```

```
ensemble =
  simulationEnsembleDatastore with properties:
    DataVariables: [4x1 string]
  IndependentVariables: [0x0 string]
  ConditionVariables: [0x0 string]
  SelectedVariables: [4x1 string]
```

```
        ReadSize: 1
        NumMembers: 5
    LastMemberRead: [0x0 string]
        Files: [5x1 string]
```

`ensemble.DataVariables`

```
ans = 4x1 string array
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
```

`ensemble.SelectedVariables`

```
ans = 4x1 string array
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
```

You can now use `ensemble` to read and analyze the generated data in the ensemble datastore. See `simulationEnsembleDatastore` for more information.

## Input Arguments

### **`simin` — Simulation configurations**

vector of `Simulink.SimulationInput` objects

Simulation configurations, specified as a vector of `Simulink.SimulationInput` objects. The simulation configurations specify parameters for each generated member of the ensemble, such as:

- Simulink model to run
- Values of model variables
- Block parameters
- Model initial state

Thus, for example, you can create a vector of `Simulink.SimulationInput` objects in which all simulation configurations are identical except for the parameters that model the presence and severity of faults in your system. You can then use the vector to generate an ensemble of simulated data representing a range of healthy and faulty operating conditions.

## Location — Folder path

`pwd` (default) | string | character vector

Folder path at which to store simulation data, specified as a string or a character vector. If you do not provide `location`, the function uses the current folder (the path returned by `pwd`).

In the specified folder, the function writes one MAT-file per simulation. Each file includes the following variables:

- `SimulationInput` — The `Simulink.SimulationInput` object that was used to configure the model for generating the data in this file. You can use this object to extract information about the conditions (such as faulty or healthy) under which this simulation was run.
- `SimulationMetadata` — Other information about the simulation that generated the logged data in the file.
- A `Dataset` object containing all the signal and state data that the Simulink model is configured to log. By default, this variable is called `logout`, but the name is configurable in the model.
- `PMSignalLogName` — The name of the variable that contains the logged data ('`logout`' by default). The `simulationEnsembleDatastore` command uses this name to parse the data in the file.

For more information about data logging, see “Export Signal Data Using Signal Logging” (Simulink).

Example: `pwd + "\simResults"`

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, . . . , NameN, ValueN`.



Example: 'UseParallel',true

### **UseParallel** — Whether to run simulations in parallel

false (default) | true

Whether to run simulations in parallel, specified as the comma-separated pair consisting of 'UseParallel' and:

- `false` — Do not run simulations in parallel.
- `true` — Use a parallel pool to run multiple simulations in parallel (requires Parallel Computing Toolbox™).

## **Output Arguments**

### **status** — Simulation error status

logical

Simulation error status, returned as a logical value:

- 1 (true) if all simulations run to completion without error
- 0 (false) otherwise

### **E** — Simulation errors

structure array

Simulation errors, returned as a structure array with fields:

- 'SimulationInput' — Simulink.SimulationInput for the simulation run that generated the error
- 'ErrorDiagnostic' — String containing the error

## **Extended Capabilities**

### **Automatic Parallel Support**

Accelerate code by automatically running computation in parallel using Parallel Computing Toolbox™.

To run in parallel, set the 'UseParallel' option to true.

## **See Also**

`Simulink.SimulationInput` | `simulationEnsembleDatastore`

## **Topics**

“Data Ensembles for Condition Monitoring and Predictive Maintenance”

**Introduced in R2018a**

# lyapunovExponent

Characterize the rate of separation of infinitesimally close trajectories

## Syntax

```
lyapExp = lyapunovExponent(X, fs)
[lyapExp, estep, ldiv] = lyapunovExponent(X, fs)
[lyapExp, estep, ldiv] = lyapunovExponent( ____, Name, Value)
```

lyapunovExponent(X, fs)

## Description

lyapExp = lyapunovExponent(X, fs) estimates the Lyapunov exponent of the uniformly sampled time-domain signal X using sampling frequency fs. Use lyapunovExponent to characterize the rate of separation of infinitesimally close trajectories in phase space to distinguish different attractors. Lyapunov exponent is useful in quantifying the level of chaos in a system, which in turn can be used to detect potential faults.

[lyapExp, estep, ldiv] = lyapunovExponent(X, fs) estimates the Lyapunov exponent, expansion step, and the corresponding logarithmic divergence of the uniformly sampled time-domain signal X. Use expansion step estep and the corresponding logarithmic divergence ldiv for signal diagnostics.

[lyapExp, estep, ldiv] = lyapunovExponent( \_\_\_\_, Name, Value) estimates the Lyapunov exponent with additional options specified by one or more Name, Value pair arguments.

lyapunovExponent(X, fs) with no output arguments creates an average logarithmic divergence versus expansion step plot.

Use the generated interactive plot to find an appropriate ExpansionRange.

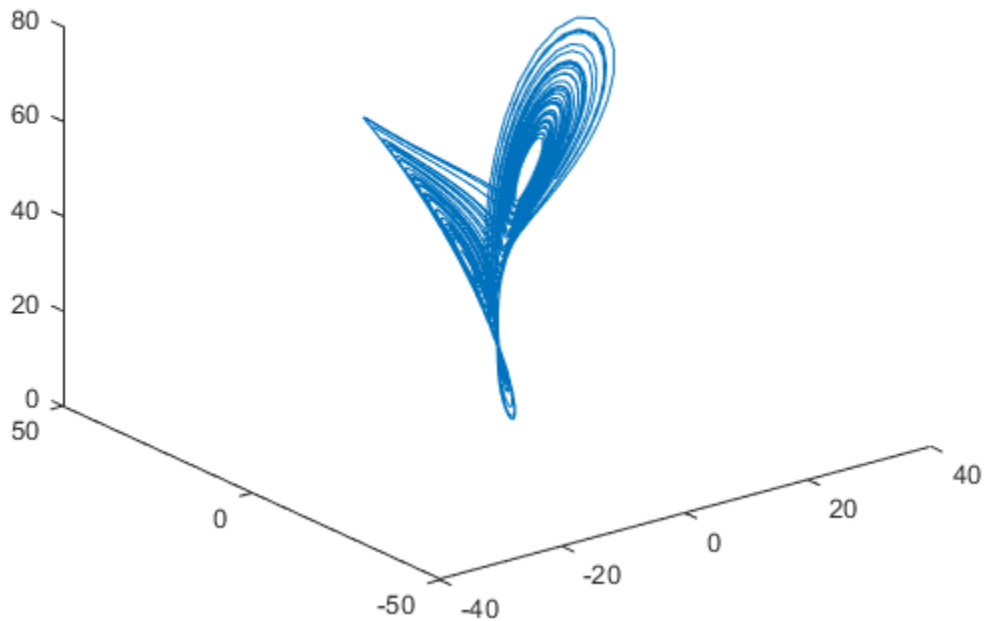
## Examples

### Visualize and Estimate Largest Lyapunov Exponent

In this example, consider a Lorenz attractor describing a unique set of chaotic solutions.

Load the data set and sampling frequency `fs` to the workspace, and visualize the Lorenz attractor in 3-D.

```
load('lorenzAttractorExampleData.mat','data','fs');  
plot3(data(:,1),data(:,2),data(:,3));
```

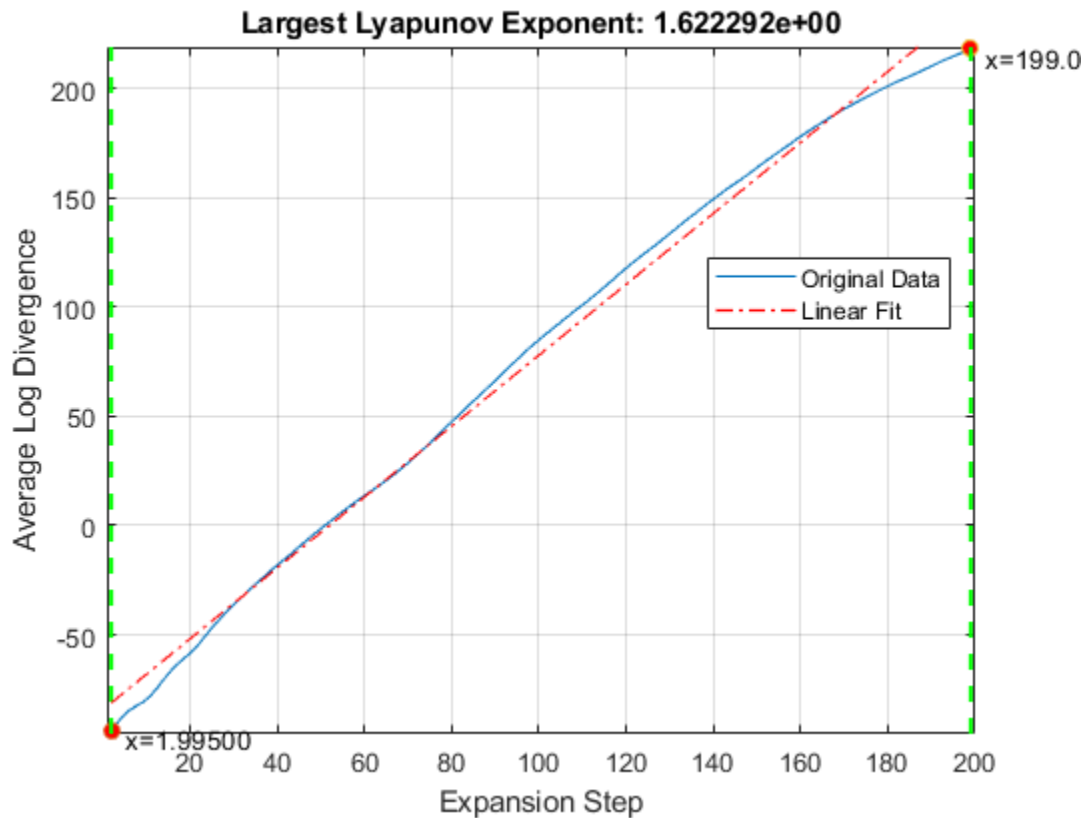


For this example, use the x-direction data of the Lorenz attractor. Since `Lag` is unknown, estimate the delay using `phaseSpaceReconstruction`. Set `Dimension` to 3 since the Lorenz attractor is a three-dimensional system. The `Dimension` and `Lag` parameters are required to create the logarithmic divergence versus expansion step plot.

```
xdata = data(:,1);  
dim = 3;  
[~,lag] = phaseSpaceReconstruction(xdata,[],dim)  
  
lag = 10
```

Create the average logarithmic divergence versus expansion step plot for the Lorenz attractor, using the `Lag` value obtained in the previous step. Set a sufficiently large expansion range to capture all the expansion steps.

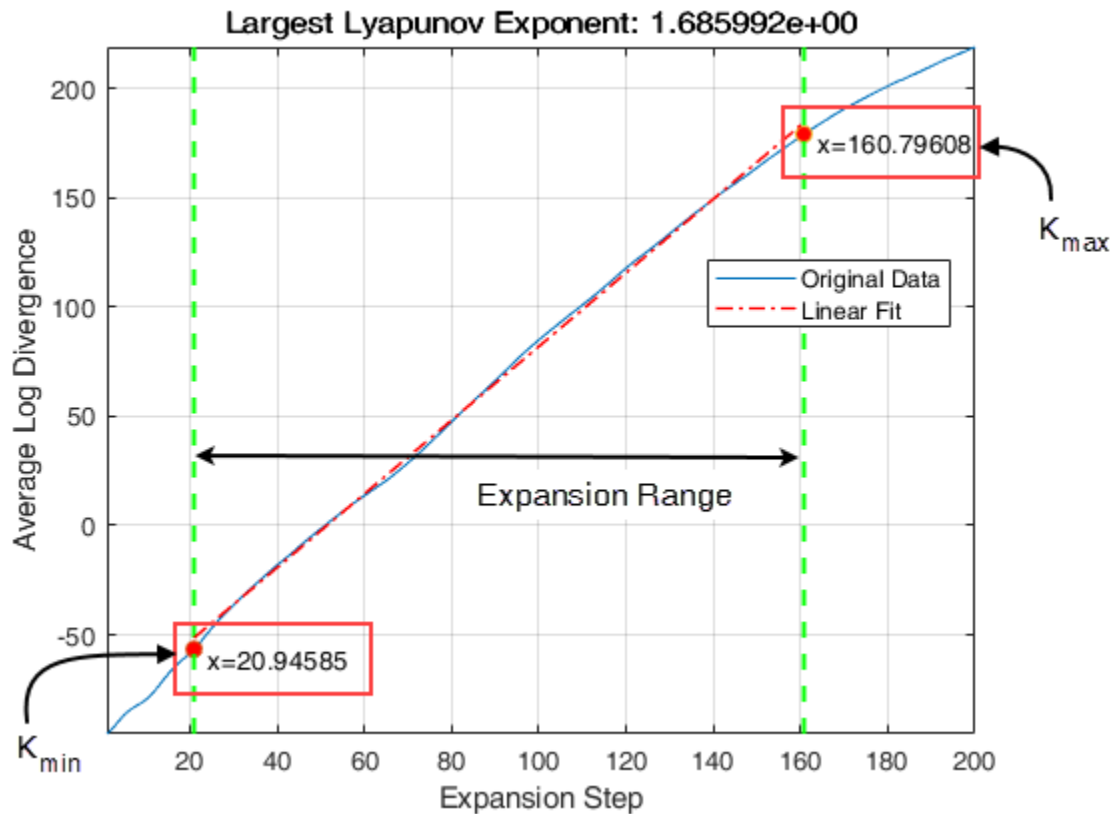
```
eRange = 200;  
lyapunovExponent(xdata,fs,'Dimension',dim,'Lag',lag,'ExpansionRange',eRange)
```



The first dashed, vertical green line (on the left) indicates the minimum number of steps used to estimate the expansion range, while the second vertical green line (on the right), represents the maximum number of steps used. Together, the first and second vertical lines represent the expansion range. The dashed red line indicates the linear fit line for the data, within the expansion range.

To compute the largest Lyapunov exponent, you first need to determine the expansion range needed for accurate estimation.

In the plot, drag the two dashed, vertical green lines to *best fit* the linear fit line to the original data line to obtain the expansion range:  $K_{\min}$  and  $K_{\max}$ .



Note the new values of the expansion range after dragging the two vertical lines for an appropriate fit.

Since expansion range can only be specified using whole numbers, round-off  $K_{\min}$  and  $K_{\max}$  to the nearest integer. Find the largest Lyapunov exponent of the Lorenz attractor using the new expansion range value.

```
Kmin = 21;
```

```
Kmax = 161;
```

```
lyapExp = lyapunovExponent(xdata, fs, 'Dimension', dim, 'Lag', lag, 'ExpansionRange', [Kmin K
```

```
lyapExp = 1.6837
```

A negative Lyapunov exponent indicates convergence, while positive Lyapunov exponents demonstrate divergence and chaos. The magnitude of `lyapExp` is an indicator of the rate of convergence or divergence of the infinitesimally close trajectories.

## Input Arguments

### **X — Uniformly sampled time-domain signal**

vector | array | timetable

Uniformly sampled time-domain signal, specified as a vector, array, or timetable. If `X` has multiple columns, `lyapunovExponent` computes the largest Lyapunov exponent by treating `X` as a multivariate signal.

If `X` is specified as a row vector, `lyapunovExponent` treats it as a univariate signal.

### **fs — Sampling frequency**

scalar

Sampling frequency, specified as a scalar. Sampling frequency or sampling rate is the average number of samples obtained in one second.

If `fs` is not supplied, a normalized frequency of  $2\pi$  is used to compute the Lyapunov exponent. If `X` is specified as a timetable, the sampling time is inferred from it.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `..., 'Dimension', 3`

### **Dimension — Embedding dimension**

2 (default) | scalar | vector

Embedding dimension, specified as the comma-separated pair consisting of `'Dimension'` and either a scalar or vector. When `Dimension` is scalar, every column in `X` is reconstructed using `Dimension`. When `Dimension` is a vector having same length as the number of columns in `X`, the reconstruction dimension for column `i` is `Dimension(i)`.



Specify `Dimension` based on the dimension of your system, that is, the number of states. For more information on embedding dimension, see `phaseSpaceReconstruction`.

### **Lag — Delay in phase space reconstruction**

1 (default) | scalar | vector

Delay in phase space reconstruction, specified as the comma-separated pair consisting of 'Lag' and either a scalar or vector. When `Lag` is scalar, every column in `X` is reconstructed using `Lag`. When `Lag` is a vector having same length as the number of columns in `X`, the reconstruction delay for column `i` is `Lag(i)`.

The default value of `Lag` is 1.

If the delay is too small, random noise is introduced in the data. In contrast, if the lag is too large, the reconstructed dynamics do not represent the true dynamics of the time series. For more information on estimating optimal delay, see `phaseSpaceReconstruction`.

### **MinSeparation — Mean period**

`ceil(fs/max(meanfreq(X,fs)))` (default) | positive scalar integer

Mean period, specified as the comma-separated pair consisting of 'MinSeparation' and a positive scalar integer.

`MinSeparation` is the threshold value used to find the nearest neighbor  $i^*$  for a point  $i$  to estimate the largest Lyapunov exponent.

The default value of `MinSeparation` is `ceil(fs/max(meanfreq(X,fs)))`.

### **ExpansionRange — Range of expansion steps**

[1, 5] (default) | 1x2 positive integer array | positive scalar integer

Range of expansion steps, specified as the comma-separated pair consisting of 'ExpansionRange' and either a 1x2 positive integer array or a positive scalar integer.

The minimum and maximum value of `ExpansionRate` is used to estimate the local expansion rate to calculate the Lyapunov exponent.

If `ExpansionRange` is specified as a scalar `M`, then the range is set to be [1, `M`]. `ExpansionRange` can only be specified using positive whole numbers and the default value is [1, 5].

## Output Arguments

### **lyapExp** — Largest Lyapunov exponent

scalar

Largest Lyapunov exponent, returned as a scalar. `lyapExp` quantifies the rate of divergence or convergence of close trajectories in phase space.

A negative Lyapunov exponent indicates convergence, while positive Lyapunov exponents demonstrate divergence and chaos. The magnitude of `lyapExp` is an indicator of the rate of convergence or divergence of the infinitesimally close trajectories.

The ability to discern levels of divergence within data sets is useful in the field of engineering to estimate component failure by studying their vibration and acoustic signals, or to predict when a ship would capsize based on its motion.[2][3]

### **estep** — Expansion step used for estimation

array

Expansion step used for estimation, returned as an array. `estep` is the difference between the maximum and minimum expansion range split into an equal number of points defined by the maximum value of `ExpansionRange`.

### **ldiv** — Logarithmic divergence

array

Logarithmic divergence, returned as an array with the same size as `estep`. The magnitude of each value in `ldiv` corresponds to the logarithmic convergence or divergence of each point in `estep`.

## Algorithms

Lyapunov exponent is calculated in the following way:

- 1 The `lyapunovExponent` function first generates a delayed reconstruction  $Y_{1:N}$  with embedding dimension  $m$ , and lag  $\tau$ .
- 2 For a point  $i$ , the software then finds the nearest neighbor point  $i^*$  that satisfies 
$$\min_{i^*} \|Y_i - Y_{i^*}\| \text{ such that } |i - i^*| > \text{MinSeparation}$$
, where `MinSeparation`, the mean period, is the reciprocal of the mean frequency.

- 3 Lyapunov exponent for the entire expansion range is calculated as,

$$\lambda(i) = \frac{1}{K_{\max} + K_{\min} + 1} \sum_{K=K_{\min}}^{K_{\max}} \frac{1}{K * dt} \ln \frac{\|Y_{i+K} - Y_{i^*+K}\|}{\|Y_i - Y_{i^*}\|}$$

where,  $K_{\min}$  and  $K_{\max}$  represent ExpansionRange, dt is the sampling time and

$$ldiv = \ln \frac{\|Y_{i+K} - Y_{i^*+K}\|}{\|Y_i - Y_{i^*}\|}$$

- 4 A single value for the Lyapunov exponent is then calculated from the above step using the polyfit command as,

$$lyapExp = \text{polyfit}([K_{\min} \ K_{\max}], \lambda(i))$$

## References

- [1] Michael T. Rosenstein , James J. Collins , Carlo J. De Luca. "A practical method for calculating largest Lyapunov exponents from small data sets ". *Physica D* 1993. Volume 65. Pages 117-134.
- [2] Caesarendra, Wahyu & Kosasih, P & Tieu, Kiet & Moodie, Craig. "An application of nonlinear feature extraction-A case study for low speed slewing bearing condition monitoring and prognosis." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics: Mechatronics for Human Wellbeing, AIM 2013*.1713-1718. 10.1109/AIM.2013.6584344.
- [3] McCue, Leigh & W. Troesch, Armin. (2011). "Use of Lyapunov Exponents to Predict Chaotic Vessel Motions". *Fluid Mechanics and its Applications*. 97. 415-432. 10.1007/978-94-007-1482-3\_23.

## See Also

approximateEntropy | correlationDimension | phaseSpaceReconstruction

Introduced in R2018a

## monotonicity

Quantify monotonic trend in condition indicators

### Syntax

```
Y = monotonicity(X)
Y = monotonicity(X, lifetimeVar)
Y = monotonicity(X, lifetimeVar, dataVar)
Y = monotonicity(X, lifetimeVar, dataVar, memberVar)
Y = monotonicity( ____, Name, Value)
```

```
monotonicity( ____ )
```

### Description

`Y = monotonicity(X)` returns the monotonicity of the lifetime data `X`. Use `monotonicity` to quantify the monotonic trend in condition indicators as the system evolves toward failure. The values of `Y` range from 0 to 1, where `Y` is 1 if `X` is perfectly monotonic and 0 if `X` is non-monotonic.

As a system gets progressively closer to failure, a suitable condition indicator typically has a monotonic trend. Conversely, any feature with a non-monotonic trend is a less suitable condition indicator.

`Y = monotonicity(X, lifetimeVar)` returns the monotonicity of the lifetime data `X` using the lifetime variable `lifetimeVar`.

`Y = monotonicity(X, lifetimeVar, dataVar)` returns the monotonicity of the lifetime data `X` using the data variables specified by `dataVar`.

`Y = monotonicity(X, lifetimeVar, dataVar, memberVar)` returns the monotonicity of the lifetime data `X` using the lifetime variable `lifetimeVar`, the data variables specified by `dataVar`, and the member variable `memberVar`.

`Y = monotonicity( ___, Name, Value)` estimates the monotonicity with additional options specified by one or more `Name, Value` pair arguments. You can use this syntax with any of the previous input-argument combinations.

`monotonicity( ___ )` with no output arguments plots a bar chart of ranked monotonicity values.

## Examples

### Monotonicity of Data in Cell Array of Matrices

In this example, consider the lifetime data of 10 identical machines with the following 6 potential prognostic parameters – constant, linear, quadratic, cubic, logarithmic, and periodic. The data set `machineDataCellArray.mat` contains `C`, which is a `1x10` cell array of matrices where each element of the cell array is a matrix that contains the lifetime data of a machine. For each matrix in the cell array, the first column contains the time while the other columns contain the data variables.

Load the lifetime data and visualize it against time.

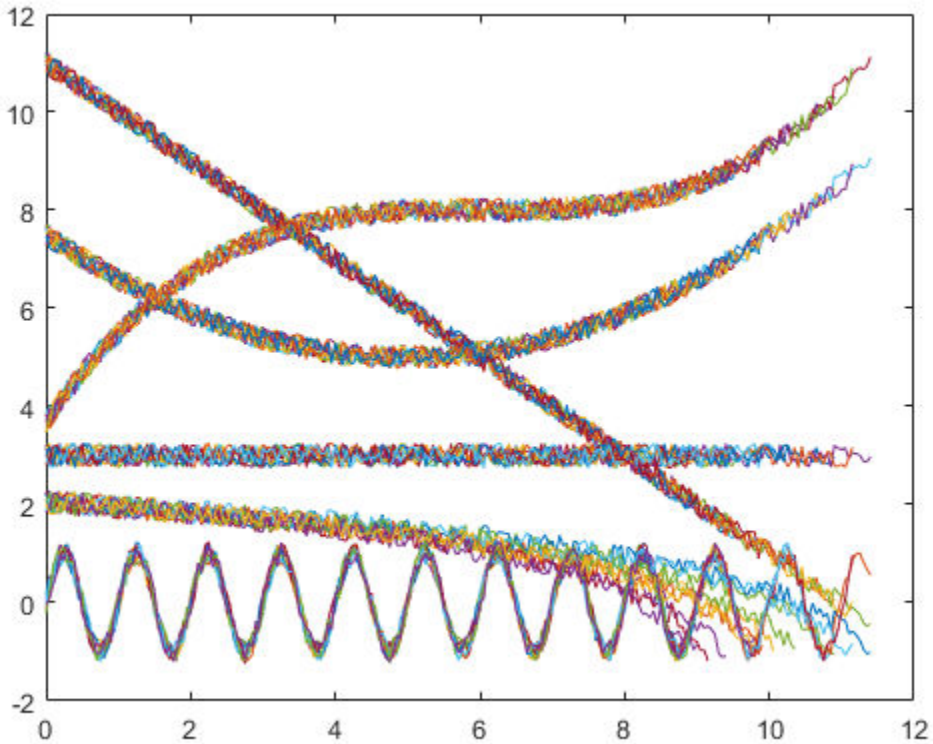
```
load('machineDataCellArray.mat','C')
display(C)
```

```
C = 1x10 cell array
  Columns 1 through 4
    {219x7 double}    {189x7 double}    {202x7 double}    {199x7 double}

  Columns 5 through 8
    {229x7 double}    {184x7 double}    {224x7 double}    {208x7 double}

  Columns 9 through 10
    {181x7 double}    {197x7 double}

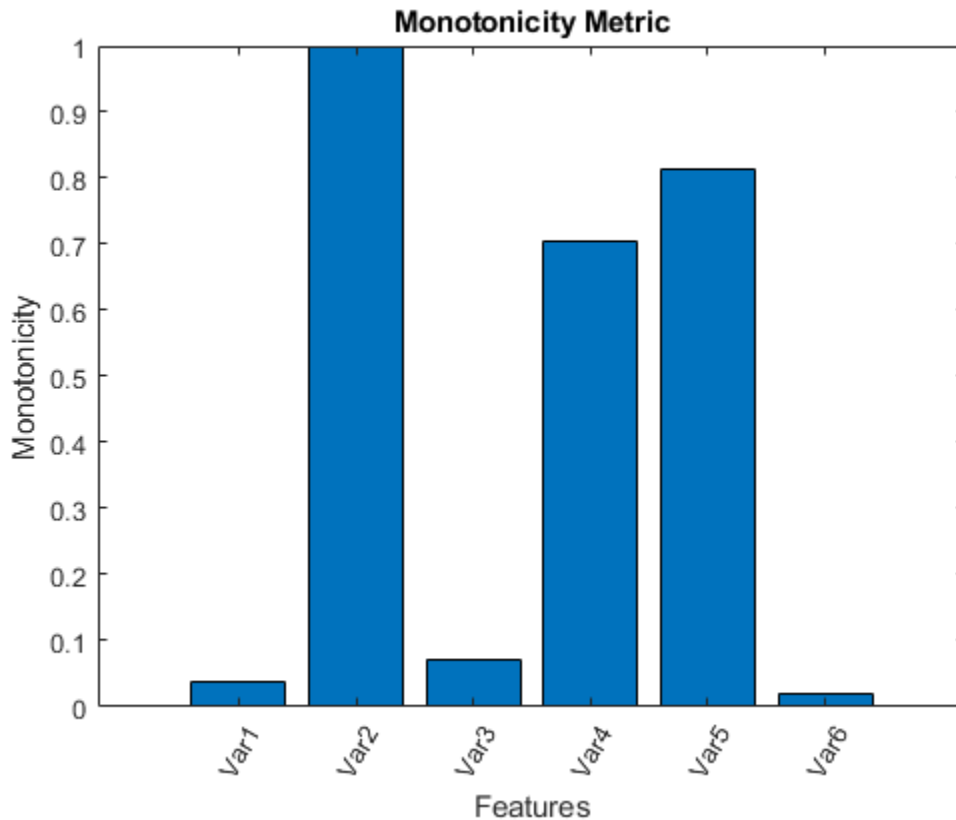
for k = 1:length(C)
    plot(C{k}(:,1), C{k}(:,2:end));
    hold on;
end
```



Observe the 6 different condition indicators—constant, linear, quadratic, cubic, logarithmic, and periodic—for all 10 machines on the plot.

Visualize the monotonicity of the potential prognostic features.

`monotonicity(C)`



From the histogram plot, observe that the features Var2, Var4 and Var5 rank better than the others. Hence, these features are more appropriate for remaining useful life predictions since they are the best indicators of machine health.

### Monotonicity of Data in Cell Array of Tables

In this example, consider the lifetime data of 10 identical machines with the following 6 potential prognostic parameters – constant, linear, quadratic, cubic, logarithmic, and periodic. The data set `machineDataTable.mat` contains `T`, which is a `1x10` cell array of

tables where each element of the cell array contains a table of lifetime data for a machine.

Load and display the data.

```
load('machineDataTable.mat','T');  
display(T)
```

```
T = 1x10 cell array  
Columns 1 through 4  
  
    {219x7 table}    {189x7 table}    {202x7 table}    {199x7 table}  
  
Columns 5 through 8  
  
    {229x7 table}    {184x7 table}    {224x7 table}    {208x7 table}  
  
Columns 9 through 10  
  
    {181x7 table}    {197x7 table}
```

```
head(T{1},2)
```

```
ans=2x7 table  
Time    Constant    Linear    Quadratic    Cubic    Logarithmic    Periodic  
-----  
    0      3.2029     11.203     7.7029     3.8829     2.2517     0.2029  
 0.05     2.8135     10.763     7.2637     3.6006     1.8579     0.12251
```

Note that every table in the cell array contains the lifetime variable 'Time' and the data variables 'Constant', 'Linear', 'Quadratic', 'Cubic', 'Logarithmic', and 'Periodic'.

Compute monotonicity using Spearman's rank correlation method with Time as the lifetime variable.

```
Y = monotonicity(T, 'Time', 'Method', 'rank')
```

```
Y=1x6 table  
Constant    Linear    Quadratic    Cubic    Logarithmic    Periodic  
-----  
-----  
-----  
-----  
-----  
-----
```



0.069487      1      0.17777      0.97993      0.99957      0.059208

From the resulting table of monotonicity values, observe that the linear, cubic, and logarithmic features have values closer to 1. Hence, these three features are more appropriate for predicting remaining useful life since they are the best indicators of machine health.

### Visualize Monotonicity of Lifetime Data in Ensemble Datastore

Consider the lifetime data of 4 machines. Each machine has 4 fault codes for the potential condition indicators—voltage, current, and power. `monotonicityEnsemble.zip` is a collection of 4 files where every file contains a timetable of lifetime data for each machine—`tbl1.mat`, `tbl2.mat`, `tbl3.mat`, and `tbl4.mat`. You can also use files containing data for multiple machines. For each timetable, the organization of the data is as follows:

Time	Voltage	Current	Power	FaultCode	Machine

Extract the compressed files, read the data in the timetables, and create a `fileEnsembleDatastore` object using the timetable data. For more information on creating a file ensemble datastore, see `fileEnsembleDatastore`.

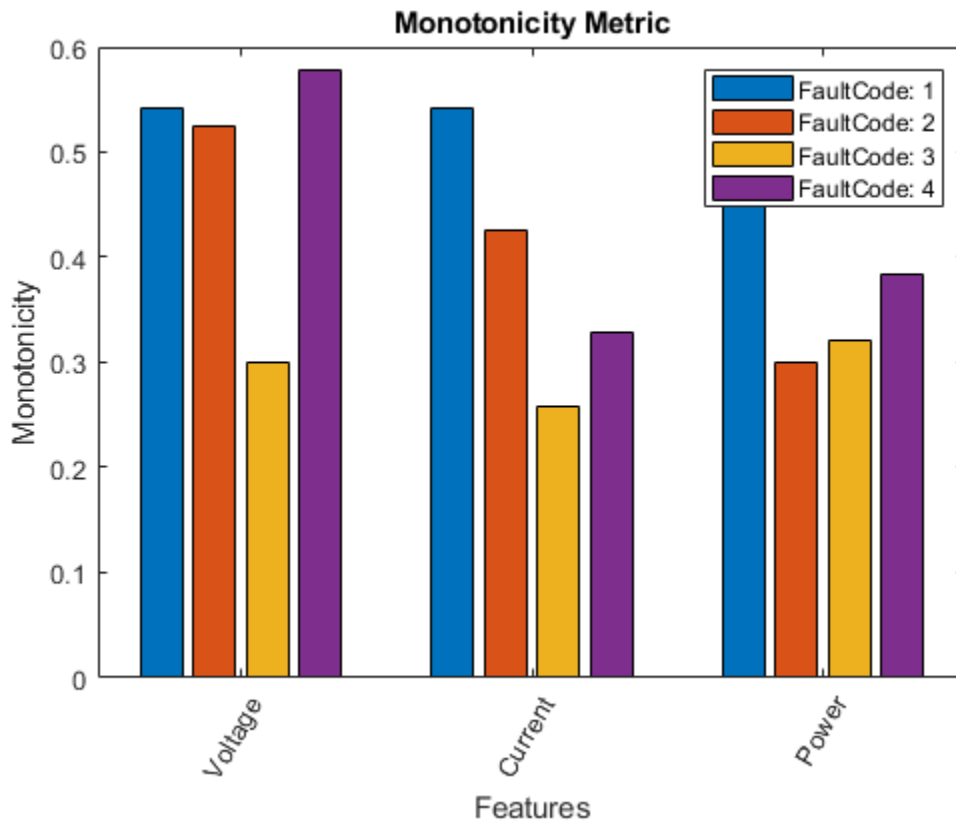
```
unzip monotonicityEnsemble.zip;
ens = fileEnsembleDatastore(pwd, '.mat');
ens.DataVariables = {'Voltage', 'Current', 'Power', 'FaultCode', 'Machine'};
% Make sure that the function for reading data is on path
addpath(fullfile(matlabroot, 'examples', 'predmaint', 'main'))
ens.ReadFcn = @readtable_data;
ens.SelectedVariables = {'Voltage', 'Current', 'Power', 'FaultCode', 'Machine'};
```

Visualize the monotonicity of the potential prognostic features with 'Machine' as the member variable and group the lifetime data by 'FaultCode'. Grouping the lifetime data ensures that `monotonicity` calculates the metric for each fault code separately.

```
monotonicity(ens, 'MemberVariable', 'Machine', 'GroupBy', 'FaultCode');
```

```
Starting parallel pool (parpool) using the 'local' profile ...
connected to 12 workers.
```

```
Evaluating tall expression using the Parallel Pool 'local':  
- Pass 1 of 1: Completed in 6.1 sec  
Evaluation completed in 9.1 sec  
Evaluating tall expression using the Parallel Pool 'local':  
- Pass 1 of 1: Completed in 2.8 sec  
Evaluation completed in 3.6 sec  
Evaluating tall expression using the Parallel Pool 'local':  
- Pass 1 of 1: Completed in 2.3 sec  
Evaluation completed in 2.3 sec
```



monotonicity returns a histogram plot with the features ranked by their monotonicity values. A higher monotonicity value indicates a more suitable prognostic parameter. For instance, the candidate feature Current has the highest monotonic trend for machines with FaultCode 1.

```
rmpath(fullfile(matlabroot, 'examples', 'predmaint', 'main')) % Reset path
```

## Input Arguments

### X — Lifetime data

cell array of matrices | cell array of tables and timetables | fileEnsembleDatastore object | table | timetable

Lifetime data, specified as a cell array of matrices, cell array of tables and timetables, fileEnsembleDatastore object, table, or timetable. Lifetime data contains run-to-failure data of the systems being monitored. The term *lifetime* here refers to the life of the machine defined in terms of the units you use to measure system life. Units of lifetime can be quantities such as the distance traveled (miles), fuel consumed (gallons), or time since the start of operation (days).

If X is

- a cell array of matrices or tables, the function assumes that each matrix or table contains columns of lifetime data for a system. Each column of every matrix or table, except the first column, contains data for a prognostic variable. 'Var1', 'Var2', ... can be used to refer to the matrix columns that contain the lifetime data. For instance, the file machineDataCellArray.mat contains a 1-by-10 cell array of matrices C, where each of the 10 matrices contains data for a particular machine.
- a table or timetable, the function assumes that each column, except the first one, contains columns of lifetime data. The table variable names can be used to refer to the columns that contain the lifetime data. If lifetimeVar is not specified when X is a table, then the first data column is used as the lifetime variable.
- a fileEnsembleDatastore object, specify the data variables dataVar and member variables memberVar to be used. If lifetimeVar is not specified, then the first data column is used as the lifetime variable for computation.

Each numerical member in X is of type double.

### lifetimeVar — Lifetime variable

string | character vector

Lifetime variable, specified as a string or character vector. lifetimeVar measures the lifetime of the systems being monitored and the lifetime data is sorted with respect to

`lifetimeVar`. The value of `lifetimeVar` must be a valid ensemble or table variable name.

For a cell array of matrices, the value 'Time' can be used to refer to the first column of each matrix, which is assumed to contain the lifetime variable. For instance, the file `machineDataCellArray.mat` contains the cell array `C`, where the first column in each matrix contains the lifetime variable while the other columns contain the data variables.

### **dataVar — Data variables**

string array | character vector | cell array of character vectors

Data variables, specified as a string array, character vector, or cell array of character vectors. Data variables are the main content of the members of an ensemble. Data variables can include measured data or derived data for the analysis and development of predictive maintenance algorithms.

If `X` is

- a `fileEnsembleDatastore` object, the value of `dataVar` supersedes the `DataVariables` property of the ensemble.
- a cell array of matrices, the value 'Time' can be used to refer to the first column of each matrix, that is, the lifetime variable `lifetimeVar`. 'Var1', 'Var2', ... can be used to refer to the other matrix columns which contain the lifetime data. For instance, the file `machineDataCellArray.mat` contains the cell array `C` where the first column in each matrix contains the lifetime variable. The other columns in the cell array `C` contain the data variables.
- a table, the table variable names can be used to refer to the columns which contain the lifetime data.

The values of `dataVar` must be valid ensemble or table variable names. If `dataVar` is not specified, the computation includes all data columns except the one specified in `lifetimeVar`. For instance, suppose that each entry in a cell array is a table with variables A, B, C, and D. Setting `dataVar` to ["A", "D"] uses only A and D for the computation while C and D are ignored.

### **memberVar — Member variable**

string | character vector

Member variable, specified as a string or character vector. Use `memberVar` to specify the variable for identifying the systems or machines in lifetime data `X`. For instance, in the `fileEnsembleDatastore` object, the fifth column in each timetable contains numbers

that identify data from a particular machine. The column name corresponds to the member variable `memberVar`.

`memberVar` is ignored when `X` is specified as a cell array of matrices or tables.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `..., 'Method', 'rank'`

### **LifeTimeVariable** — Lifetime variable

`strings(0)` (default) | string | character vector

Lifetime variable, specified as the comma-separated pair consisting of `'LifeTimeVariable'` and either a string or character vector. If `'LifeTimeVariable'` is not specified, then the first data column is used.

`'LifeTimeVariable'` is equivalent to the input argument `lifetimeVar`.

### **DataVariables** — Data variables

`strings(0)` (default) | string array | character vector | cell array of character vectors

Data variables, specified as the comma-separated pair consisting of `'DataVariables'` and either a string array, character vector or cell array of character vectors.

`'DataVariables'` is equivalent to the input argument `dataVar`.

### **MemberVariable** — Member variables

`[]` (default) | string | character vector

Member variables, specified as the comma-separated pair consisting of `'MemberVariable'` and either a string or character vector.

`'MemberVariable'` is equivalent to the input argument `memberVar`.

### **GroupBy** — Grouping criterion

`[]` (default) | string | character vector

Grouping criterion, specified as the comma-separated pair consisting of 'GroupBy' and either a string or character vector. Use 'GroupBy' to specify the variables for grouping the lifetime data  $X$  by operating conditions.

The function computes the metric separately for each group that results from applying the criterion, such as a fault condition, specified by 'GroupBy'. For instance, in the `fileEnsembleDatastore` object `ens`, the fourth column in each timetable in `ens` contains the variable 'FaultCode'. The metric is computed for each machine by grouping the data by 'FaultCode'.

You can only group variables when  $X$  is defined as a `fileEnsembleDatastore` object, table, timetable, or cell array of tables or timetables.

### **WindowSize — Size of the centered moving average window for data smoothing**

`[]` (default) | scalar | two-element vector

Size of the centered moving average window for data smoothing, specified as the comma-separated pair consisting of 'WindowSize' and either a scalar or two-element vector. A Savitzky-Golay filter is used for data smoothing. For more information, see `smoothdata`.

If 'WindowSize' is not specified, the window length is automatically determined from lifetime data  $X$  using `smoothdata(X, 'sgolay')`. Set 'WindowSize' to 0 to turn off data smoothing.

### **Method — Method to compute monotonicity**

'sign' (default) | 'rank'

Method to compute monotonicity, specified as the comma-separated pair consisting of 'Method' and either 'sign' or 'rank'.

- 'sign', Use the signum formula.
- 'rank', Use Spearman's rank correlation formula.

For more information, see “Algorithms” on page 1-59.

## **Output Arguments**

### **Y — Monotonicity of lifetime data**

vector | table

Monotonicity of lifetime data, returned as a vector or table.

`monotonicity` characterizes the trend of a feature as the system evolves toward failure. As a system gets progressively closer to failure, a suitable condition indicator typically has a monotonic trend. Conversely, any feature with a non-monotonic trend is a less suitable condition indicator. The values of `Y` range from 0 to 1.

- `Y` is 1 if `X` is perfectly monotonic.
- `Y` is 0 if `X` is perfectly non-monotonic.

Selecting appropriate estimation parameters out of all available features is the first step in building a reliable remaining useful life prediction engine. The monotonicity values in `Y` are useful to determine which condition indicators best track the degradation process of the systems being monitored. The higher the monotonic trend, the more desirable the feature is for prognostics.

When 'GroupBy' is not specified, then `Y` is returned as a row vector or single-row table. Conversely, when 'GroupBy' is specified, then each row in `Y` corresponds to one group.

## Limitations

- When `X` is a tall table or tall timetable, `monotonicity` nevertheless loads the complete array into memory using `gather`. If the memory available is inadequate, then `monotonicity` returns an error.

## Algorithms

Monotonicity is computed in the following two ways as specified by the 'Method' option.

### Signum Formula or Sign Method

When you specify 'Method' as 'sign', the computation of monotonicity uses this formula:

$$\text{monotonicity} = \frac{1}{M} \sum_{j=1}^M \left| \sum_{k=1}^{N_j-1} \frac{\text{sgn}(x_j(k+1) - x_j(k))}{N_j - 1} \right|$$

where  $x_j$  represents the vector of measurements of a feature on the  $j^{\text{th}}$  system,  $M$  is the number of systems monitored, and  $N_j$  is the number of measurements on the  $j^{\text{th}}$  system.

## Spearman's Rank Correlation Coefficient Method

When you specify 'Method' as 'rank', the computation of monotonicity uses this formula:

$$monotonicity = \frac{1}{M} \sum_{j=1}^M \left| \text{corr}(\text{rank}(x_j), \text{rank}(t_j)) \right|$$

where  $M$  is the number of systems monitored and  $t_j$  is the vector of time points corresponding to the measurement vector  $x_j$ .

## References

- [1] Coble, J., and J. W. Hines. "Identifying Optimal Prognostic Parameters from Data: A Genetic Algorithms Approach." In *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. 2009.
- [2] Coble, J. "Merging Data Sources to Predict Remaining Useful Life - An Automated Method to Identify Prognostics Parameters." Ph.D. Thesis. University of Tennessee, Knoxville, TN, 2010.
- [3] Lei, Y. *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Xi'an, China: Xi'an Jiaotong University Press, 2017.
- [4] Lofti, S., J. B. Ali, E. Bechhoefer, and M. Benbouzid. "Wind turbine high-speed shaft bearings health prognosis through a spectral Kurtosis-derived indices and SVR." *Applied Acoustics* Vol. 120, 2017, pp. 1-8.

## See Also

fileEnsembleDatastore | prognosability | trendability

## Topics

"Wind Turbine High-Speed Bearing Prognosis"

**Introduced in R2018b**



# phaseSpaceReconstruction

Convert observed time series to state vectors

## Syntax

```
XR = phaseSpaceReconstruction(X,lag,dim)
[XR,eLag,eDim] = phaseSpaceReconstruction(X)
[XR,eLag,eDim] = phaseSpaceReconstruction(X,lag)
[XR,eLag,eDim] = phaseSpaceReconstruction(X,[],dim)
[ ___ ] = phaseSpaceReconstruction( ___,Name,Value)

phaseSpaceReconstruction( ___ )
```

## Description

`XR = phaseSpaceReconstruction(X,lag,dim)` returns the reconstructed phase space `XR` of the uniformly sampled time-domain signal `X` with time delay `lag` and embedding dimension `dim` as inputs.

Use `phaseSpaceReconstruction` to verify the system order and reconstruct all dynamic system variables, while preserving system properties. Reconstructing the phase space is useful when limited data is available, or when the phase space dimension and lag is unknown. The nonlinear features `approximateEntropy`, `correlationDimension`, and `lyapunovExponent` use `phaseSpaceReconstruction` as the first step of the computation.

`[XR,eLag,eDim] = phaseSpaceReconstruction(X)` returns reconstructed phase space `XR` along with the estimated delay `eLag` and embedding dimension `eDim`.

`[XR,eLag,eDim] = phaseSpaceReconstruction(X,lag)` returns the reconstructed phase space `XR` of uniformly sampled time domain signal `X` and embedding dimension `eDim` using time delay specified by `lag`.

`[XR,eLag,eDim] = phaseSpaceReconstruction(X,[],dim)` returns the reconstructed phase space `XR` of uniformly sampled time domain signal `X` and time delay `eLag` using embedding dimension specified by `dim`.

[ \_\_\_ ] = `phaseSpaceReconstruction( ___ ,Name,Value)` returns the reconstructed phase space XR with additional options specified by one or more Name,Value pair arguments.

`phaseSpaceReconstruction( ___ )` with no output arguments creates a matrix of sub-axes of the reconstructed phase space with histogram plots along the diagonal.

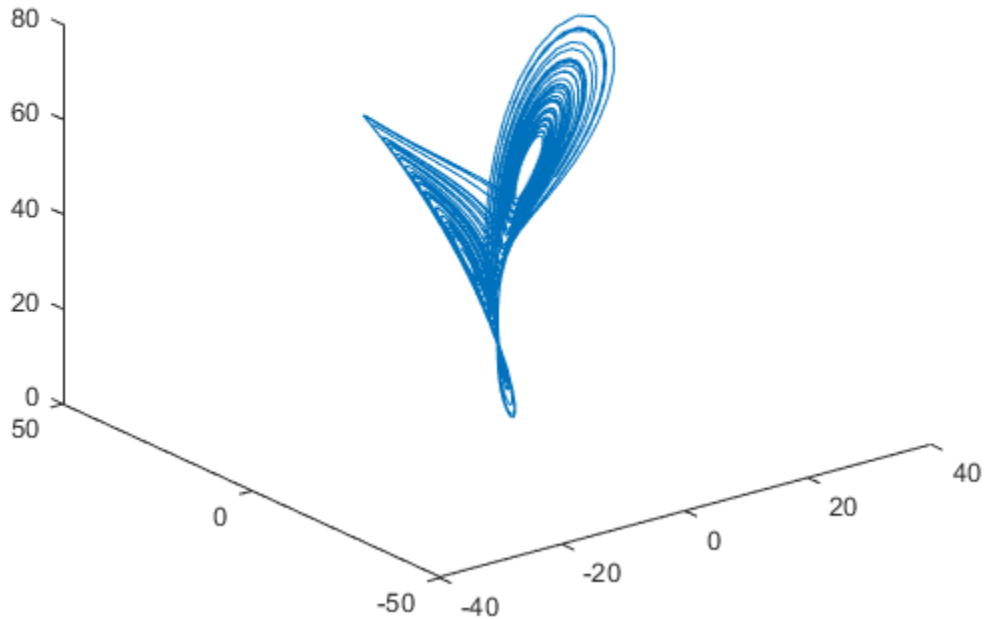
## Examples

### Reconstruct Data using Phase Space Reconstruction

In this example, assume that you have measurements for a Lorenz Attractor. Your measurements are along the x direction only, but the attractor is a three-dimensional system. Using this limited data, reconstruct the phase space such that the properties of the original system are preserved.

Load the Lorenz Attractor data and visualize its x, y and z measurements on a 3-D plot.

```
load('lorenzAttractorExampleData.mat','data');  
plot3(data(:,1),data(:,2),data(:,3));
```



Estimate the lag and dimension using the x-direction measurement.

```
xdata = data(:,1);  
[~,eLag,eDim] = phaseSpaceReconstruction(xdata)
```

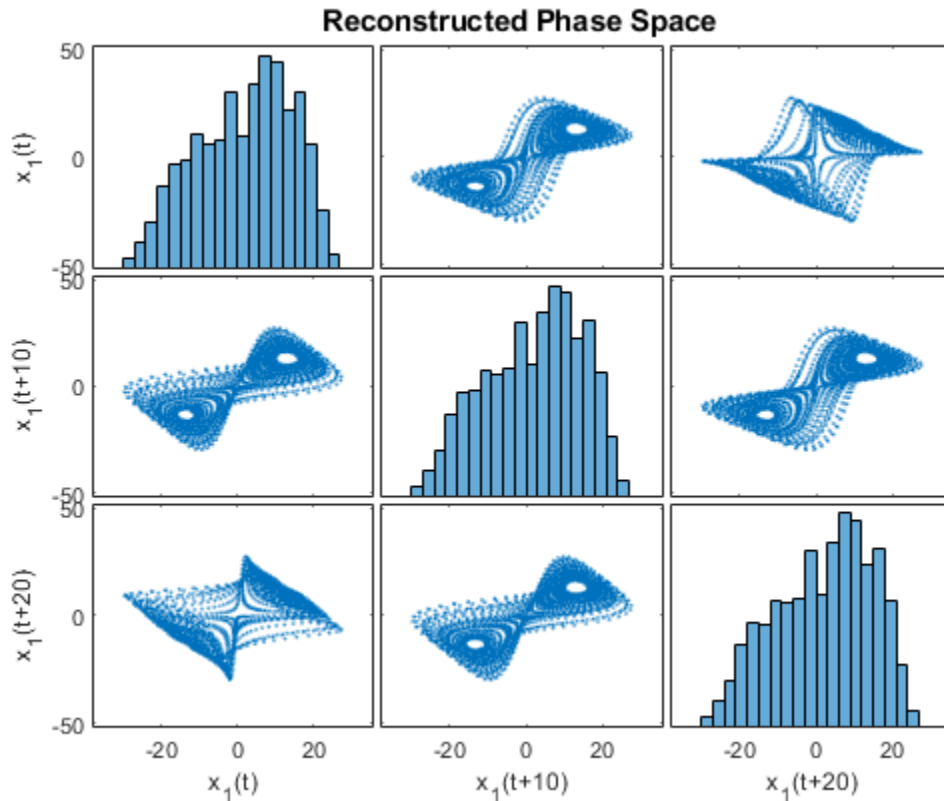
```
eLag = 10
```

```
eDim = 3
```

Since the Lorenz Attractor has data in 3 dimensions, the estimated embedding dimension `eDim` is 3.

Visualize the reconstructed phase space using the estimated lag and embedding dimension.

```
phaseSpaceReconstruction(xdata, eLag, eDim);
```



As observed from the 3x3 phase space plot, the topology of the attractor is recovered.  $x_1(t+10)$  and  $x_1(t+20)$  are the other two states reconstructed with the estimated lag value of 10. The diagonal plots (1,1), (2,2) and (3,3) represent the histogram of  $x_1(t)$ ,  $x_1(t+10)$  and  $x_1(t+20)$  data, respectively.

## Input Arguments

### **X — Uniformly sampled time-domain signal**

vector | array | timetable

Uniformly sampled time-domain signal, specified as a vector, array, or timetable. When multiple columns exist in *X*, each column is treated as an independent time series.

If *X* is specified as a row vector, `phaseSpaceReconstruction` treats it as a univariate signal.

### **dim — Embedding dimension**

scalar | vector

Embedding dimension, specified as a scalar or vector. *dim* is the dimension of the space in which you reconstruct a phase portrait starting from your measurements.

When *dim* is scalar, every column in *X* is reconstructed using *dim*. When *dim* is a vector having same length as the number of columns in *X*, the reconstruction dimension for column *i* is *dim(i)*.

### **lag — Delay value used in phase space reconstruction**

scalar | vector

Delay value used in phase space reconstruction, specified as a scalar or vector. When *lag* is scalar, every column in *X* is reconstructed using *lag*. When *lag* is a vector having same length as the number of columns in *X*, the reconstruction delay for column *i* is *lag(i)*.

If the time delay is too small, random noise is introduced in the states. In contrast, if the lag is too large, the reconstructed dynamics do not represent the true dynamics of the time series.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of *Name*, *Value* arguments. *Name* is the argument name and *Value* is the corresponding value. *Name* must appear inside quotes. You can specify several name and value pair arguments in any order as *Name1*, *Value1*, ..., *NameN*, *ValueN*.

Example: ... 'HistogramBins', 12

## **HistogramBins — Number of bins for discretization**

10 (default) | scalar

Number of bins for discretization, specified as the comma-separated pair consisting of 'HistogramBins' and a scalar. HistogramBins is required to compute the Average Mutual Information (AMI) to estimate delay eLag.

Set the value of HistogramBins based on the length of X.

## **MaxLag — Maximum value of lag**

10 (default) | scalar

Maximum value of lag, specified as the comma-separated pair consisting of 'MaxLag' and a scalar. MaxLag is used to estimate delay est\_delay using the Average Mutual Information (AMI) algorithm.

## **PercentFalseNeighbors — Factor to determine embedding dimension**

0.1 (default) | scalar

Factor to determine embedding dimension, specified as the comma-separated pair consisting of 'PercentFalseNeighbors' and a scalar. When percentage of false nearest neighbors drops below the tuning parameter PercentFalseNeighbors at a dimension d, d is considered as the embedding dimension.

The default value of PercentFalseNeighbors is 0.1 and permissible values lie within the range 0 through 1.

## **DistanceThreshold — Distance threshold to determine false neighbors**

10 (default) | scalar

Distance threshold to determine false neighbors, specified as the comma-separated pair consisting of 'DistanceThreshold' and a scalar. DistanceThreshold is a tuning parameter to determine the number of points that are false nearest neighbors in the reconstructed phase space.

The default value of DistanceThreshold is 10, and suggested values lie within the range 10 through 50.

## **MaxDim — Maximum value of embedding dimension**

5 (default) | scalar

Maximum value of embedding dimension, specified as the comma-separated pair consisting of 'MaxDim' and a scalar.

Change the value of `MaxDim` if the number of states of your system exceeds 5.

## Output Arguments

### **XR — Reconstructed phase space**

array | timetable

Reconstructed phase space, returned as either an array or timetable. XR contains state vectors based on the embedding dimension and lag value.

### **eLag — Estimated time delay**

scalar

Estimated time delay, returned as a scalar, regardless of the size of X.

`eLag` is estimated using Average Mutual Information (AMI) algorithm. For more information, see “Algorithms” on page 1-67.

### **eDim — Estimated embedding dimension**

scalar

Estimated embedding dimension, returned as a scalar, regardless of the size of X.

`eDim` is estimated using False Nearest Neighbor (FNN) algorithm. For more information, see “Algorithms” on page 1-67.

## Algorithms

### **Phase Space Reconstruction**

For a uniformly sampled univariate time signal  $X_1 = (x_{1,1}, x_{1,2}, \dots, x_{1,N})^T$ , phaseSpaceReconstruction computes the delayed reconstruction

$$X_{1,i}^r = (x_{1,i}, x_{1,i+\tau_1}, \dots, x_{1,i+(m_1-1)\tau_1}), \quad i = 1, 2, \dots, N - (m_1 - 1)\tau_1$$

where,  $N$  is the length of the time series,  $\tau_1$  is the lag, and  $m_1$  is the embedding dimension for  $X_1$ .

Similarly, for a multivariate time series  $X$  given by,

$$X = [X_1, X_2, \dots, X_S] = \begin{bmatrix} x_{1,1} & \dots & x_{S,1} \\ \vdots & \ddots & \vdots \\ x_{1,N} & \dots & x_{S,N} \end{bmatrix}$$

`phaseSpaceReconstruction` computes the reconstruction for each time series as,

$$X_i^r = (X_{1,i}^r, X_{2,i}^r, \dots, X_{S,i}^r), \quad i = 1, 2, \dots, N - (\max\{m_i\} - 1)(\max\{\tau_i\})$$

where  $S$  is the number of measurements, and  $N$  is the length of the time series.

### Delay Estimation

The delay for phase space reconstruction is estimated using Average Mutual Information (AMI). For reconstruction, the time delay is set to be the first local minimum of AMI.

Average Mutual Information is computed as,

$$AMI(T) = \sum_{i=1}^N p(x_i, x_{i+T}) \log_2 \left[ \frac{p(x_i, x_{i+T})}{p(x_i) p(x_{i+T})} \right]$$

where,  $N$  is the length of the time series and  $T = 1:\text{MaxLag}$ .

### Embedding Dimension Estimation

The embedding dimension for phase space reconstruction is estimated using False Nearest Neighbor (FNN) algorithm.

- For a point  $i$  at dimension  $d$ , the points  $X_i^r$  and its nearest point  $X_i^{r*}$  in the reconstructed phase space  $\{X_i^r\}$ ,  $i = 1:N$ , are false neighbors if

$$\sqrt{\frac{R_i^2(d+1) - R_i^2(d)}{R_i^2(d)}} > \text{DistanceThreshold}$$

where,  $R_i^2(d) = \|X_i^r - X_i^{r*}\|^2$  is the distance metric.



- The estimated embedding dimension  $d$  is the smallest value that satisfies the condition  $p_{fnn} < \text{PercentFalseNeighbors}$  where,  $p_{fnn}$  is the ratio of FNN points to total number of points in the reconstructed phase space.

## References

- [1] Rhodes, Carl & Morari, Manfred. "False Nearest Neighbors Algorithm and Noise Corrupted Time Series." *Physical Review. E*. 55.10.1103/PhysRevE.55.6162.
- [2] Kliková, B., and Aleš Raidl. "Reconstruction of phase space of dynamical systems using method of time delay." *Proceedings of the 20th Annual Conference of Doctoral Students WDS 2011*.
- [3] I. Vlachos, D. Kugiumtzis, "State Space Reconstruction for Multivariate Time Series Prediction", *Nonlinear Phenomena in Complex Systems*, Vol 11, No 2, pp 241-249, 2008.
- [4] Kantz, H., and Schreiber, T. *Nonlinear Time Series Analysis*. Cambridge: Cambridge University Press, Vol. 7, 2004.

## See Also

`approximateEntropy` | `correlationDimension` | `lyapunovExponent`

**Introduced in R2018a**

## plot

Plot survivor function for covariate survival remaining useful life model

## Syntax

```
plot mdl  
plot mdl, covariates
```

## Description

`plot mdl` plots the baseline survivor function of the fitted covariate survival model `mdl` against the life time value for which it was computed. The plot data is stored in the `BaselineCumulativeHazard` property of `mdl`.

`plot mdl, covariates` plots the survivor function computed for the covariate data in `covariates`. To obtain the survivor function, the hazard rate is computed using the `covariates` and combined with the baseline survivor function.

## Examples

### Train Covariate Survival Model

Load training data.

```
load('covariateData.mat')
```

This data contains battery discharge times and related covariate information. The covariate variables are:

- Temperature
- Load
- Manufacturer

The manufacturer information is a categorical variable that must be encoded.

Create a covariate survival model.

```
mdl = covariateSurvivalModel;
```

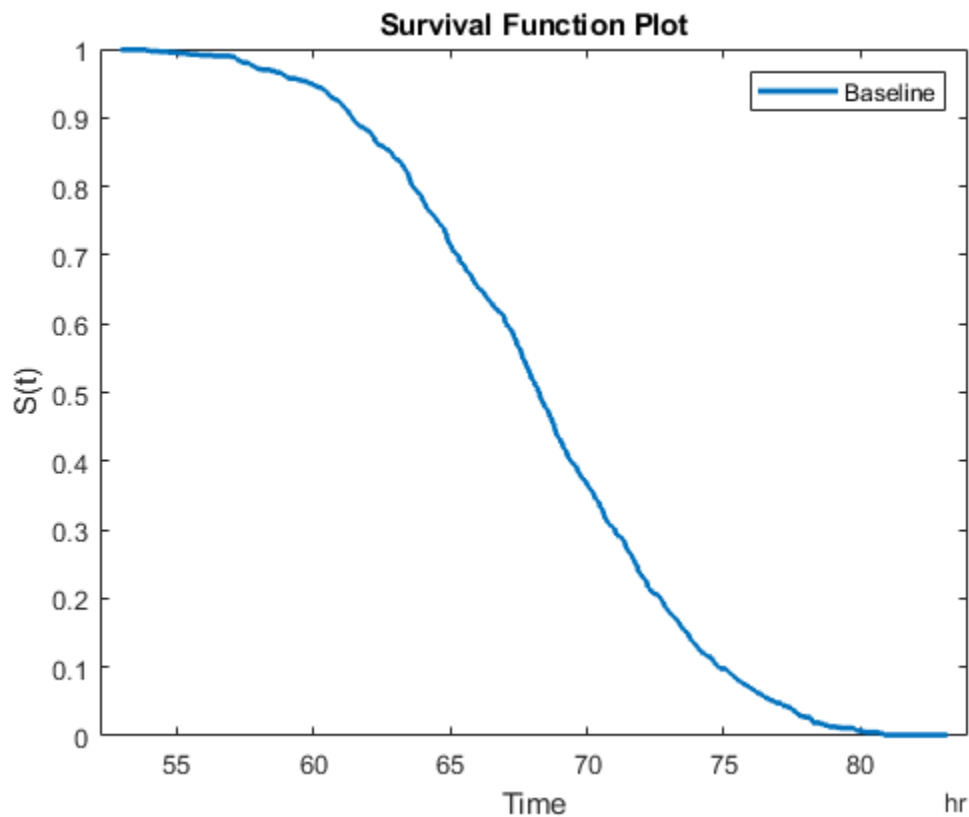
Train the survival model using the training data, specifying the life time variable, data variables, and encoded variable. There is no censor variable for this training data.

```
fit(mdl,covariateData,"DischargeTime",["Temperature","Load","Manufacturer"],[],"Manufac
```

Successful convergence: Norm of gradient less than OPTIONS.TolFun

Plot the baseline survivor function for the model.

```
plot(mdl)
```



## Predict RUL Using Covariate Survival Model

Load training data.

```
load('covariateData.mat')
```

This data contains battery discharge times and related covariate information. The covariate variables are:

- Temperature
- Load
- Manufacturer

The manufacturer information is a categorical variable that must be encoded.

Create a covariate survival model, and train it using the training data.

```
mdl = covariateSurvivalModel('LifeTimeVariable',"DischargeTime",'LifeTimeUnit',"hours",  
    'DataVariables',["Temperature","Load","Manufacturer"],'EncodedVariables',"Manufacturer");  
fit(mdl,covariateData)
```

```
Successful convergence: Norm of gradient less than OPTIONS.TolFun
```

Suppose you have a battery pack manufactured by maker B that has run for 30 hours. Create a test data table that contains the usage time, `DischargeTime`, and the measured ambient temperature, `TestAmbientTemperature`, and current drawn, `TestBatteryLoad`.

```
TestBatteryLoad = 25;  
TestAmbientTemperature = 60;  
DischargeTime = hours(30);  
TestData = timetable(TestBatteryLoad,TestAmbientTemperature,'B','RowTimes',hours(30));  
TestData.Properties.VariableNames = {'Temperature','Load','Manufacturer'};  
TestData.Properties.DimensionNames{1} = 'DischargeTime';
```

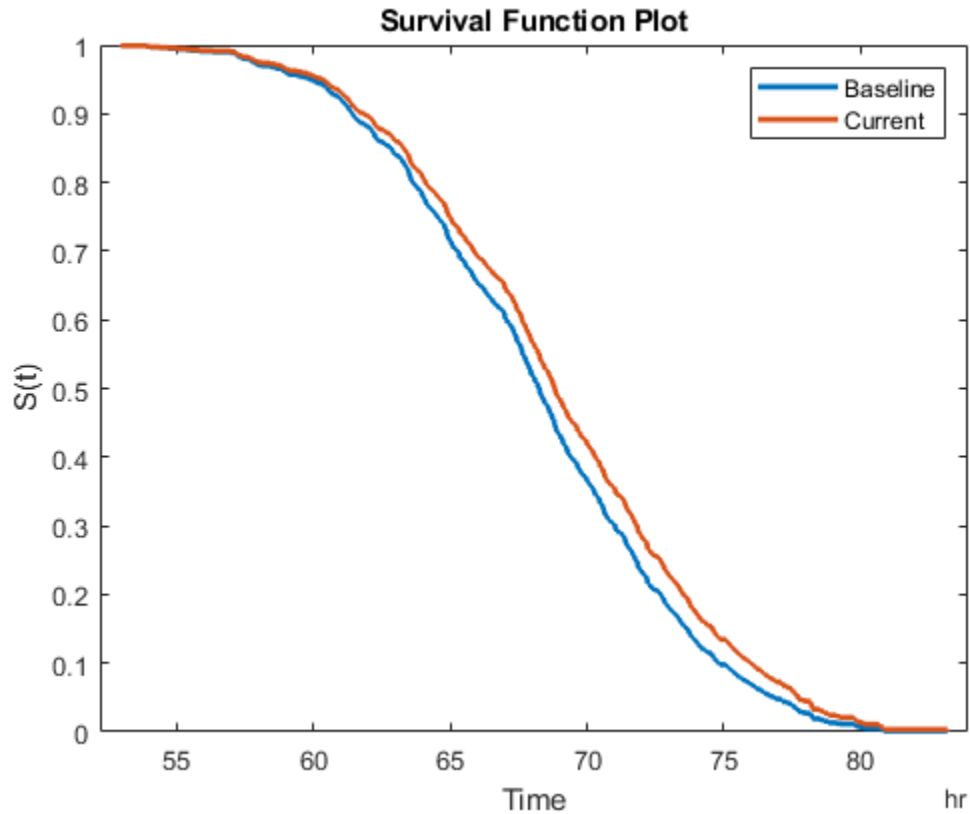
Predict the RUL for the battery.

```
estRUL = predictRUL(mdl,TestData)
```

```
estRUL = duration  
    38.657 hr
```

Plot the survivor function for the covariate data of the battery.

```
plot(md1, TestData)
```



## Input Arguments

**md1** — Covariate survival RUL model

covariateSurvivalModel object

Covariate survival RUL model, specified as a covariateSurvivalModel object.

`plot` plots the data in the `BaselineCumulativeHazard` property of `mdl`, which is a two-column array. The second column contains the baseline survivor functions values, and the first column contains the corresponding life time values. The life time values are plotted in the units specified by the `LifeTimeUnits` property of `mdl`.

### **covariates — Current covariate values**

`row vector` | `table with one row` | `timetable with one row`

Current covariate values for the component, specified as a:

- Row vector whose elements specify the component covariate values only and not the life time values. The number of covariate values must match the number and order of the covariate data columns used when estimating `mdl` using `fit`.
- `table` or `timetable` with one row. The table must contain the variables specified in the `DataVariables` property of `mdl`.

If the covariate data contains encoded variables, then you must specify `covariates` using a `table` or `timetable`.

To obtain the survivor function, the hazard rate is computed using the `covariates` and combined with the baseline survivor function. For more information, see “Cox Proportional Hazards Model” (Statistics and Machine Learning Toolbox).

## **See Also**

### **Functions**

`covariateSurvivalModel` | `coxphfit` | `predictRUL`

### **Topics**

“Cox Proportional Hazards Model” (Statistics and Machine Learning Toolbox)

**Introduced in R2018a**

# predictRUL

Estimate remaining useful life for a test component

The `predictRUL` function estimates the remaining useful life (RUL) of a test component given an estimation model and information about its usage time and degradation profile. Before predicting the RUL, you must first configure your estimation model using historical data regarding the health of an ensemble of similar components, such as multiple machines manufactured to the same specifications. To do so, use the `fit` function.

Using `predictRUL`, you can estimate the remaining useful life for the following types of estimation models:

- Degradation models
- Survival models
- Similarity models

For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life using these models, see “RUL Estimation Using RUL Estimator Models”.

## Syntax

```
estRUL = predictRUL mdl, data
estRUL = predictRUL mdl, data, bounds
estRUL = predictRUL mdl, threshold
estRUL = predictRUL mdl, usageTime
estRUL = predictRUL mdl, covariates
estRUL = predictRUL( ____, Name, Value)
[estRUL, ciRUL] = predictRUL( ____ )
```

```
[estRUL,ciRUL,pdfRUL] = predictRUL( ___ )  
[estRUL,ciRUL,pdfRUL,histRUL] = predictRUL( ___ )
```

## Description

`estRUL = predictRUL mdl, data` estimates the remaining useful life for a component using similarity model `mdl` and the degradation feature profiles in `data`. `data` contains feature measurements over the life span of the component up to the current life time.

`estRUL = predictRUL mdl, data, bounds` estimates the remaining useful life for a component using a similarity model and the feature bounds specified in `bounds`.

`estRUL = predictRUL mdl, threshold` estimates the RUL for a component using degradation model `mdl` and the current life time variable value stored in `mdl`. The RUL is the remaining time before the forecasted response of the model reaches the threshold value `threshold`.

`estRUL = predictRUL mdl, usageTime` estimates the RUL for a component using reliability survival model `mdl` and the current usage time for the component.

`estRUL = predictRUL mdl, covariates` estimates the RUL of a component using covariate survival model `mdl` and the current covariate values for the component.

`estRUL = predictRUL( ___, Name, Value)` specifies additional options using one or more name-value pair arguments.

`[estRUL,ciRUL] = predictRUL( ___ )` returns the confidence interval associated with the RUL estimation.

`[estRUL,ciRUL,pdfRUL] = predictRUL( ___ )` returns the probability density function for the RUL estimation.

`[estRUL,ciRUL,pdfRUL,histRUL] = predictRUL( ___ )` returns the histogram of component similarity scores when estimating RUL using a similarity model.

## Examples



## Train Pairwise Similarity Model

Load training data.

```
load('pairwiseTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create a pairwise similarity model with default settings.

```
mdl = pairwiseSimilarityModel;
```

Train the similarity model using the training data.

```
fit(mdl,pairwiseTrainVectors)
```

## Update Linear Degradation Model and Predict RUL

Load observation data.

```
load('linTestData.mat','linTestData1')
```

For this example, assume that the training data is not historical data, but rather real-time observations of the component condition.

Based on knowledge of the degradation feature limits, define a threshold condition indicator value that indicates the end-of-life of a component.

```
threshold = 60;
```

Create a linear degradation model arbitrary prior distribution data and a specified noise variance. Also, specify the life time and data variable names for the observation data.

```
mdl = linearDegradationModel('Theta',1,'ThetaVariance',1e6,'NoiseVariance',0.003,...
    'LifeTimeVariable',"Time",'DataVariables',"Condition",...
    'LifeTimeUnit',"hours");
```

Observe the component condition for 50 hours, updating the degradation model after each observation.

```
for i=1:50
    update mdl, linTestData1(i, :);
end
```

After 50 hours, predict the RUL of the component using the current life time value stored in the model.

```
estRUL = predictRUL(mdl, threshold)
```

```
estRUL = duration
        59.406 hr
```

The estimated RUL is about 60 hours, which indicates a total predicted life span of 110 hours.

## Predict RUL Using Exponential Degradation Model

Load training data.

```
load('expTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Hours" variable and corresponding degradation feature measurements in the "Condition" variable.

Create an exponential degradation model, specifying the life time variable units.

```
mdl = exponentialDegradationModel('LifeTimeUnit', "hours");
```

Train the degradation model using the training data. Specify the names of the life time and data variables.

```
fit(mdl, expTrainTables, "Time", "Condition")
```

Load testing data, which is a run-to-failure degradation profile for a test component. The test data is a table with the same life time and data variables as the training data.

```
load('expTestData.mat')
```

Based on knowledge of the degradation feature limits, define a threshold condition indicator value that indicates the end-of-life of a component.

```
threshold = 500;
```

Assume that you measure the component condition indicator every hour for 150 hours. Update the trained degradation model with each measurement. Then, predict the remaining useful life of the component at 150 hours. The RUL is the forecasted time at which the degradation feature will pass the specified threshold.

```
for t = 1:150
    update mdl, expTestData(t,:)
end
estRUL = predictRUL(mdl, threshold)

estRUL = duration
        136.63 hr
```

The estimated RUL is around 137 hours, which indicates a total predicted life span of 287 hours.

## Predict RUL Using Covariate Survival Model

Load training data.

```
load('covariateData.mat')
```

This data contains battery discharge times and related covariate information. The covariate variables are:

- Temperature
- Load
- Manufacturer

The manufacturer information is a categorical variable that must be encoded.

Create a covariate survival model, and train it using the training data.

```
mdl = covariateSurvivalModel('LifeTimeVariable', "DischargeTime", 'LifeTimeUnit', "hours",
    'DataVariables', ["Temperature", "Load", "Manufacturer"], 'EncodedVariables', "Manufacturer")
fit(mdl, covariateData)
```

```
Successful convergence: Norm of gradient less than OPTIONS.TolFun
```

Suppose you have a battery pack manufactured by maker B that has run for 30 hours. Create a test data table that contains the usage time, `DischargeTime`, and the measured ambient temperature, `TestAmbientTemperature`, and current drawn, `TestBatteryLoad`.

```
TestBatteryLoad = 25;
TestAmbientTemperature = 60;
DischargeTime = hours(30);
TestData = timetable(TestBatteryLoad,TestAmbientTemperature,'B','RowTimes',hours(30));
TestData.Properties.VariableNames = {'Temperature','Load','Manufacturer'};
TestData.Properties.DimensionNames{1} = 'DischargeTime';
```

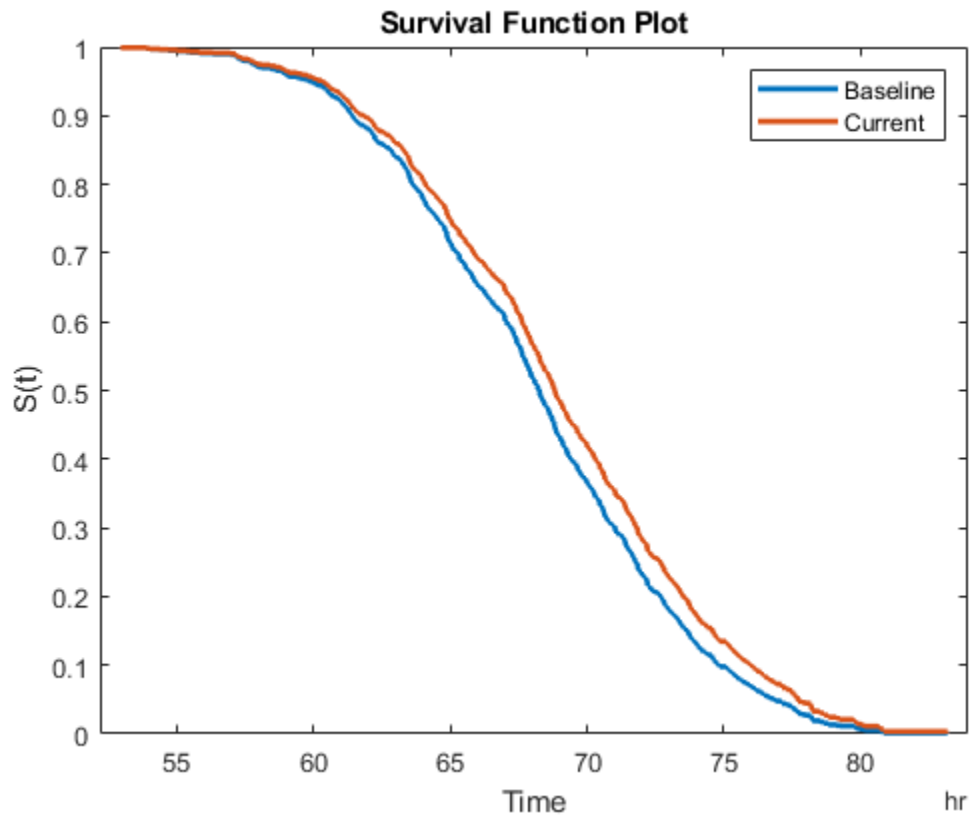
Predict the RUL for the battery.

```
estRUL = predictRUL mdl,TestData)
```

```
estRUL = duration
    38.657 hr
```

Plot the survivor function for the covariate data of the battery.

```
plot(mdl,TestData)
```



### Predict RUL Using Reliability Survival Model and View PDF

Load training data.

```
load('reliabilityData.mat')
```

This data is a column vector of duration objects representing battery discharge times.

Create a reliability survival model, specifying the life time variable and life time units.

```
mdl = reliabilitySurvivalModel('LifeTimeVariable', "DischargeTime", 'LifeTimeUnit', "hours")
```

Train the survival model using the training data.

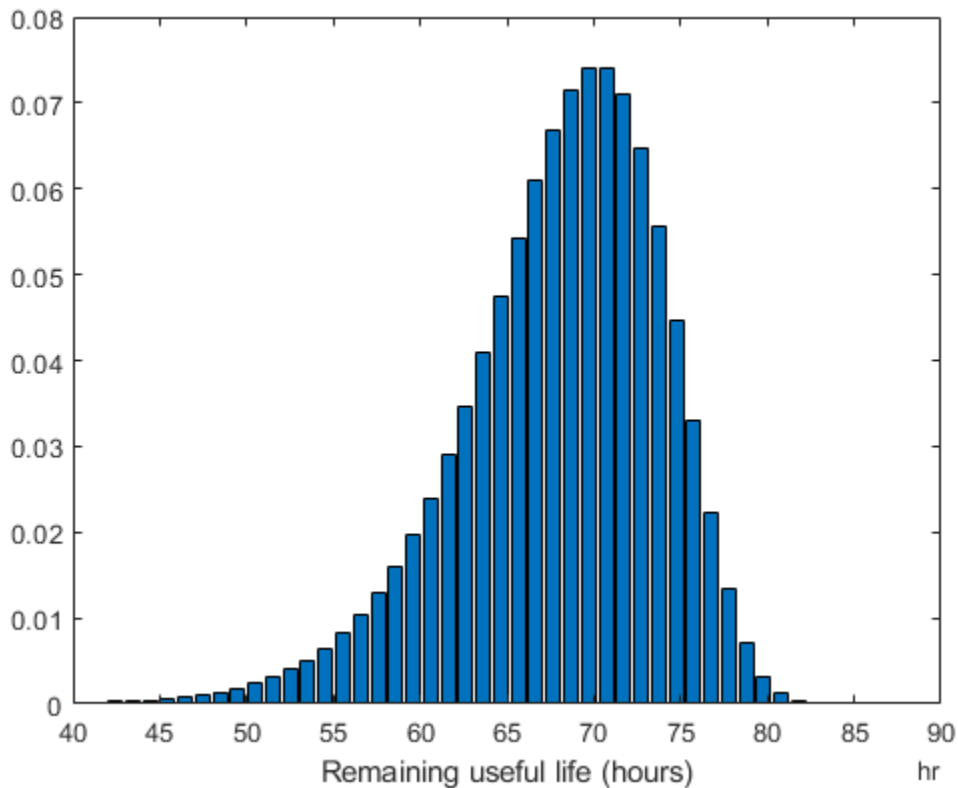
```
fit mdl, reliabilityData)
```

Predict the life span of a new component, and obtain the probability distribution function for the estimate.

```
[estRUL, ciRUL, pdfRUL] = predictRUL( mdl );
```

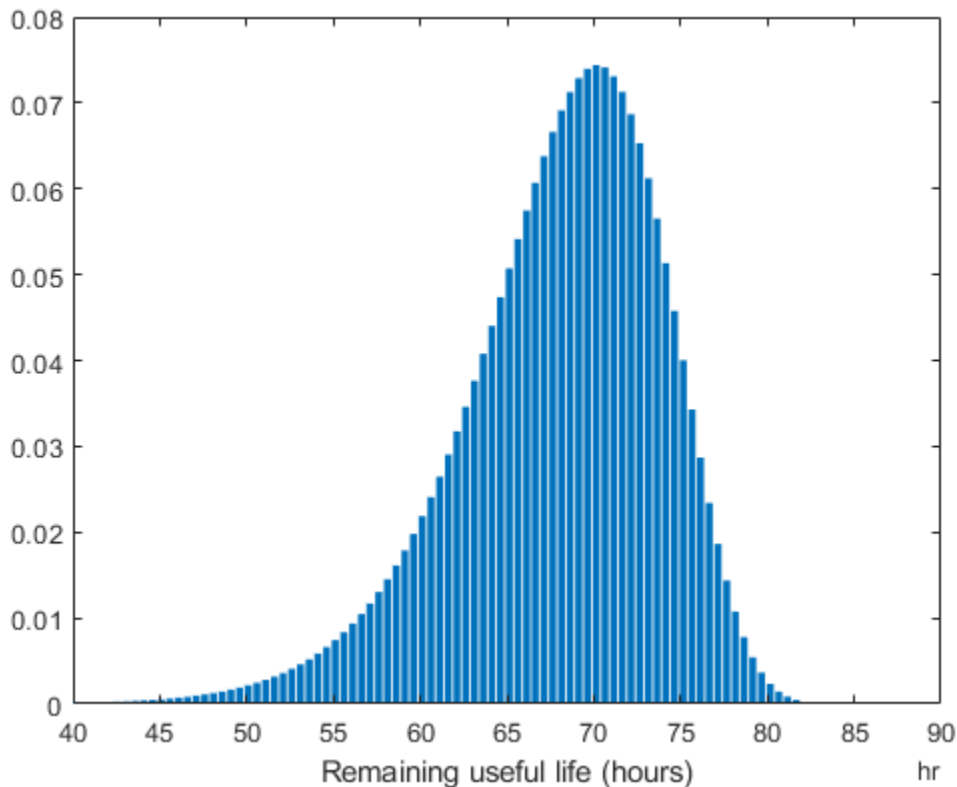
Plot the probability distribution.

```
bar( pdfRUL.RUL, pdfRUL.ProbabilityDensity )  
xlabel( 'Remaining useful life (hours)' )  
xlim( hours( [40 90] ) )
```



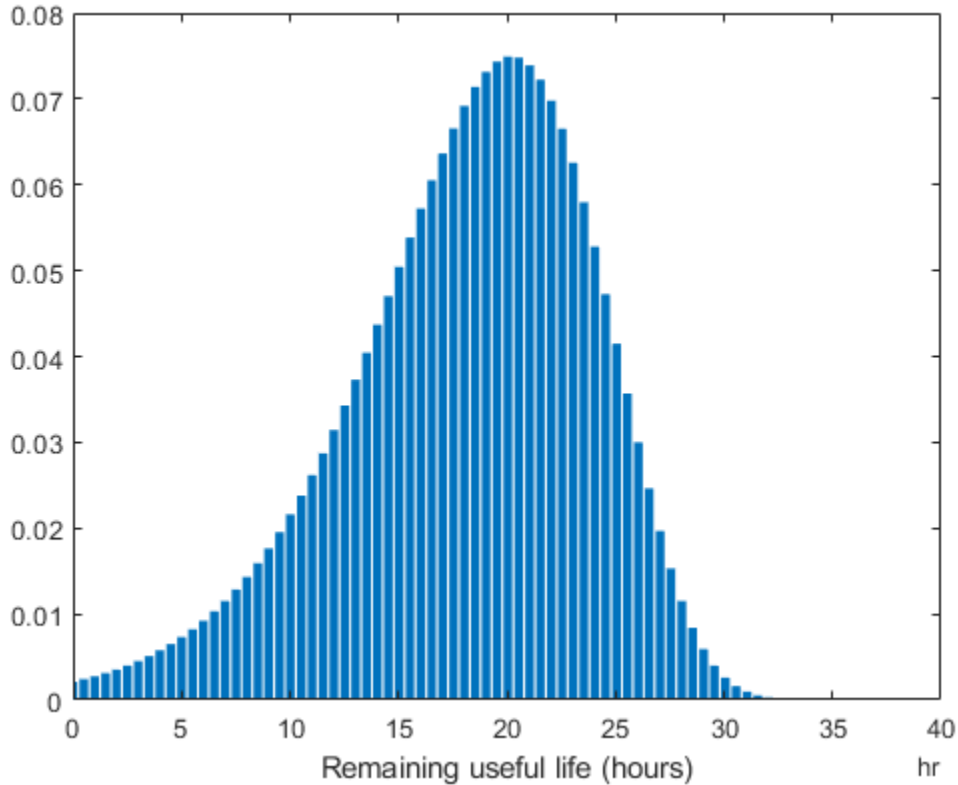
Improve the distribution view by providing the number of bins and bin size for the prediction.

```
[estRUL,ciRUL,pdfRUL] = predictRUL mdl, 'BinSize',0.5, 'NumBins',500);
bar(pdfRUL.RUL,pdfRUL.ProbabilityDensity)
xlabel('Remaining useful life (hours)')
xlim(hours([40 90]))
```



Predict the RUL for a component that has been operating for 50 hours.

```
[estRUL,ciRUL,pdfRUL] = predictRUL(mdl, hours(50), 'BinSize',0.5, 'NumBins',500);
bar(pdfRUL.RUL,pdfRUL.ProbabilityDensity)
xlabel('Remaining useful life (hours)')
xlim(hours([0 40]))
```



## Input Arguments

### **mdl** — Remaining useful life prediction model

degradation model | survival model | similarity model

Remaining useful life prediction model, specified as one of the following models.

RUL Model Groups	More Information
Degradation models	<code>linearDegradationModel</code>



RUL Model Groups	More Information
	exponentialDegradationModel
Survival models	reliabilitySurvivalModel
	covariateSurvivalModel
Similarity models	hashSimilarityModel
	pairwiseSimilarityModel
	residualSimilarityModel

For more information on the different model types and when to use them, see “Models for Predicting Remaining Useful Life”.

#### **data — Degradation feature measurements**

array | table | timetable

Degradation feature profiles for estimating the RUL using similarity models, measured over the life span of a component up to its current life time, specified as one of the following:

- $(N+1)$ -by- $M$  numeric array, where  $N$  is the number of features and  $M$  is the number of feature measurements. In each row, the first column contains the usage time and the remaining columns contain the corresponding degradation feature measurements. The order of the features must match the order specified in the `DataVariables` property of `mdl`.
- `table` or `timetable` object. The table must contain variables with names that match the strings in the `DataVariables` and `LifeTimeVariable` properties of `mdl`.

`data` applies when `mdl` is a `hashSimilarityModel`, `pairwiseSimilarityModel`, or `residualSimilarityModel`, object.

#### **bounds — Degradation feature bounds**

scalar | two-column array

Degradation feature bounds, which indicate the effective life span of a component, specified as an  $N$ -by-2 array, where  $N$  is the number of degradation features. For the  $i$ th feature, `bounds(i, 1)` is the lower bound on the feature and `bounds(i, 2)` is the upper bound. The order of the features must match the order specified in the `DataVariables` property of `mdl`.

Select bounds based on your knowledge of the allowable bounds for the degradation features.

`bounds` applies when `mdl` is a `hashSimilarityModel`, `pairwiseSimilarityModel`, or `residualSimilarityModel` object.

### **threshold — Data variable threshold**

scalar

Data variable threshold limits for degradation models, specified as a scalar value. The remaining useful life is the remaining time before the forecasted response of the model reaches the threshold value.

The sign of the `Theta` property of `mdl` indicates the direction of degradation growth. If `Theta` is:

- Positive, then `threshold` is an upper bound on the degradation feature
- Negative, then `threshold` is a lower bound on the degradation feature

Select `threshold` based on your knowledge of the allowable bounds for the degradation feature.

`threshold` applies when `mdl` is a `linearDegradationModel` or `exponentialDesgradationModel` object.

### **usageTime — Current usage time**

scalar | duration object

Current usage time of the component, specified as a scalar value or a duration object. The units of `usageTime` must be compatible with the `LifeTimeUnit` property of `mdl`.

### **covariates — Current covariate values and usage time**

row vector | table with one row | timetable with one row

Current covariate values and usage time for the component, specified as a:

- Row vector whose first column contains the usage time. The remaining columns specify the component covariate values only and not the life time values. The number of covariate values must match the number and order of the covariate data columns used when estimating `mdl` using `fit`.
- `table` or `timetable` with one row. The table must contain the variables specified in the `LifeTimeVariable`, `DataVariables`, and `CensorVariable` properties of `mdl`.

If the covariate data contains encoded variables, then you must specify covariates using a table or timetable.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `Alpha, 0.2` sets the prediction confidence interval to the  $0.2/2$  to  $1-0.2/2$  percentile region.

### Alpha — Confidence level

0.1 (default) | scalar value in the range 0 to 1

Confidence level for computing `ciRUL`, specified as the comma-separated pair consisting of 'Alpha' and a scalar value in the range 0-1. `predictRUL` computes the confidence interval as the  $\text{Alpha}/2$  to  $1-\text{Alpha}/2$  percentile region.

### NumBins — Number of bins

100 value (default) | positive integer

Number of bins used to evaluate `pdfRUL`, specified as the comma-separated pair consisting of 'NumBins' and a positive integer. This argument applies when `mdl` is a degradation model or survival model.

### BinSize — Bin size

1 (default) | positive scalar | duration object

Bin size used to determine the life span for computing `pdfRUL`, specified as the comma-separated pair consisting of 'BinSize' and either a positive scalar or a duration object. This argument applies when `mdl` is a degradation model or reliability survival model.

### Method — Survival function conversion method

'empirical' (default) | 'weibull'

Survival function conversion method for generating the probability density function of a covariate survival model, specified as the comma-separated pair consisting of 'Method' and one of the following:

- `'empirical'` — Generate `pdfRUL` by finding the gradient of the empirical cumulative distribution function. The cumulative distribution function is  $1-S(t)$ , where  $S(t)$  is the survival function.
- `'weibull'` — Generate `pdfRUL` by fitting a Weibull distribution to the survival function.

For more information on survival functions, see `covariateSurvivalModel`.

## Output Arguments

### **estRUL** — Estimated remaining useful life

scalar

Estimated remaining useful life of a component, returned as a scalar. The returned value is in the units of the life time variable as indicated by the `LifeTimeUnit` property of `mdl`.

### **ciRUL** — Confidence interval

two-element row vector

Confidence interval associated with `estRUL`, returned as a two-element row vector. Specify the percentile for the confidence interval using `Alpha`.

### **pdfRUL** — RUL probability density function

`timetable` | `table`

RUL probability density function, returned as a `timetable` if the life time variable of `mdl` is time-based, or as a `table` otherwise.

The life span used by `predictRUL` when computing the probability density function depends on the type of RUL model you specify. If `mdl` is a:

- Degradation model, then the life span is `[usageTime usageTime + BinSize*NumBins]`.
- Reliability survival model, then the life span is `[T T+BinSize*NumBins]`, where `T` is the usage time specified in `usageTime`.
- Covariate survival model, then the life span is `linspace(T1,T2,NumBins)`, where `[T1,T2]` is the life range of components as determined by the `BaselineCumulativeHazard` property of `mdl`.

- Similarity model, then the life span depends on the life spans of the nearest neighbors found by the search algorithm. For example, if the `NumNearestNeighbors` property of `mdl` is 10 and the 10 nearest neighbors have life times in the range of 10 months to three years, then the histogram of failure times is found across this range. `predictRUL` then fits a probability density function to the raw histogram data using a kernel smoothing approach.

### **histRUL — Raw similarity scores**

`timetable` | `table`

Raw similarity scores for histogram plotting, returned as a `timetable` if the life time variable of `mdl` is time-based, or as a `table` otherwise. `histRUL` has the following variables:

- `'RUL'` — Remaining useful life values of historical components used to fit the parameters of `mdl`.
- `'NormalizedDistanceScore'` — Similarity scores obtained by comparing the test component to the historical components used to fit the parameters of `mdl`.

The histogram of the data in `histRUL` is the unfitted version of `pdfRUL`. To plot the histogram, at the MATLAB command line, type:

```
bar(histRUL.RUL,histRUL.NormalizedDistanceScore)
```

`histRUL` is returned when `mdl` is a `hashSimilarityModel`, `pairwiseSimilarityModel`, or `residualSimilarityModel` object.

## **Compatibility Considerations**

### **currentValue syntax not recommended**

*Not recommended starting in R2018b*

The following syntax is not recommended:

```
estRUL = predictRUL(mdl,currentValue,threshold)
```

For a trained degradation model `mdl`, this syntax estimates the remaining useful life (RUL) based on the current measured value `currentValue` of a condition indicator. A more reliable way to estimate RUL for degradation models is to update the model with

each successive measurement of the condition indicator using the `update` command. Then, use the updated model to estimate the RUL.

Suppose that you store successive condition indicator measurements in an array `TestData`. The array contains measurements at regular intervals at least up to the time `currentTime` for which `currentValue` is the condition indicator measurement. To update your code, replace:

```
estRUL = predictRUL mdl, currentValue, threshold)
```

with the following code:

```
for t = 1:CurrentTime
    update(mdl, TestData(t, :))
end
estRUL = predictRUL(mdl, threshold)
```

For an example, see “Predict RUL Using Exponential Degradation Model” on page 1-78.

## See Also

`fit` | `update`

## Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**

# prognosability

Measure of variability of condition indicators at failure

## Syntax

```
Y = prognosability(X)
Y = prognosability(X,lifetimeVar)
Y = prognosability(X,lifetimeVar,dataVar)
Y = prognosability(X,lifetimeVar,dataVar,memberVar)
Y = prognosability( ____,Name,Value)

prognosability( ____ )
```

## Description

`Y = prognosability(X)` returns the prognosability of the lifetime data `X`. Use `prognosability` as a measure of the variability of a feature at failure based on the trajectories of the feature measured in several run-to-failure experiments. A more prognosable feature has less variation at failure relative to the range between its initial and final values. The values of `Y` range from 0 to 1, where `Y` is 1 if `X` is perfectly prognosable and 0 if `X` is non-prognosable.

`Y = prognosability(X,lifetimeVar)` returns the prognosability of the lifetime data `X` using the lifetime variable `lifetimeVar`.

`Y = prognosability(X,lifetimeVar,dataVar)` returns the prognosability of the lifetime data `X` using the data variables specified by `dataVar`.

`Y = prognosability(X,lifetimeVar,dataVar,memberVar)` returns the prognosability of the lifetime data `X` using the lifetime variable `lifetimeVar`, the data variables specified by `dataVar`, and the member variable `memberVar`.

`Y = prognosability( ____,Name,Value)` estimates the prognosability with additional options specified by one or more `Name,Value` pair arguments. You can use this syntax with any of the previous input-argument combinations.

`prognosability( ___ )` with no output arguments plots a bar chart of ranked prognosability values.

## Examples

### Prognosability of Data in Cell Array of Matrices

In this example, consider the lifetime data of 10 identical machines with the following 6 potential condition indicators—constant, linear, quadratic, cubic, logarithmic, and periodic. The data set `machineDataCellArray.mat` contains `C` which is a `1x10` cell array of matrices where each element of the cell array is a matrix that contains the lifetime data of a machine. For each matrix in the cell array, the first column contains the time while the other columns contain the data variables.

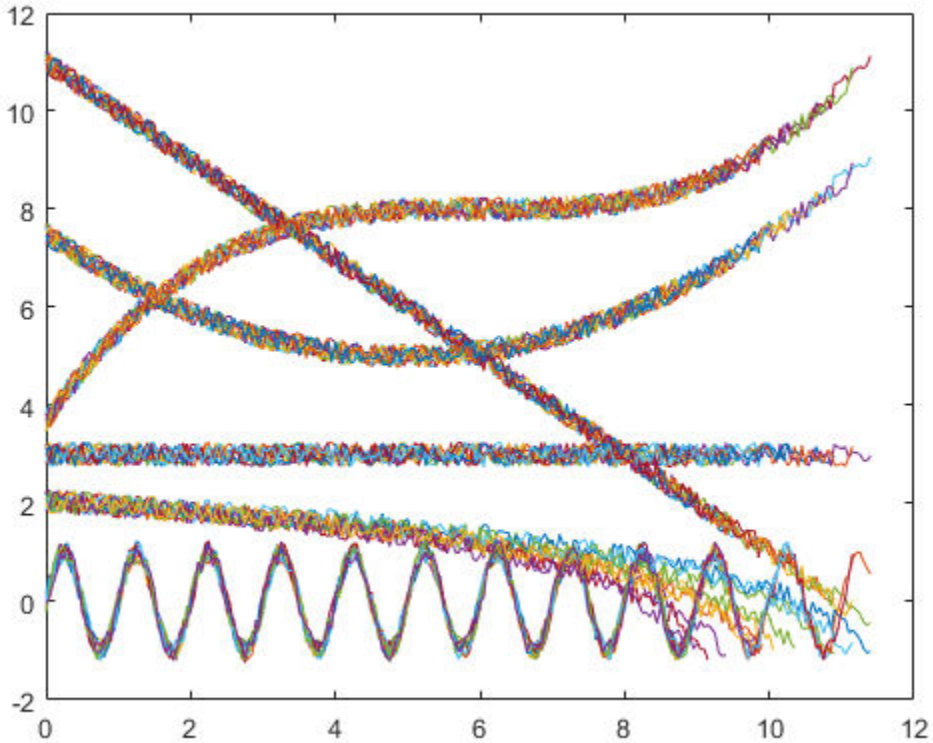
Load the lifetime data and visualize it against time.

```
load('machineDataCellArray.mat','C')
display(C)
```

```
C = 1x10 cell array
  Columns 1 through 4
    {219x7 double}    {189x7 double}    {202x7 double}    {199x7 double}
  Columns 5 through 8
    {229x7 double}    {184x7 double}    {224x7 double}    {208x7 double}
  Columns 9 through 10
    {181x7 double}    {197x7 double}

for k = 1:length(C)
    plot(C{k}(:,1), C{k}(:,2:end));
    hold on;
end
```

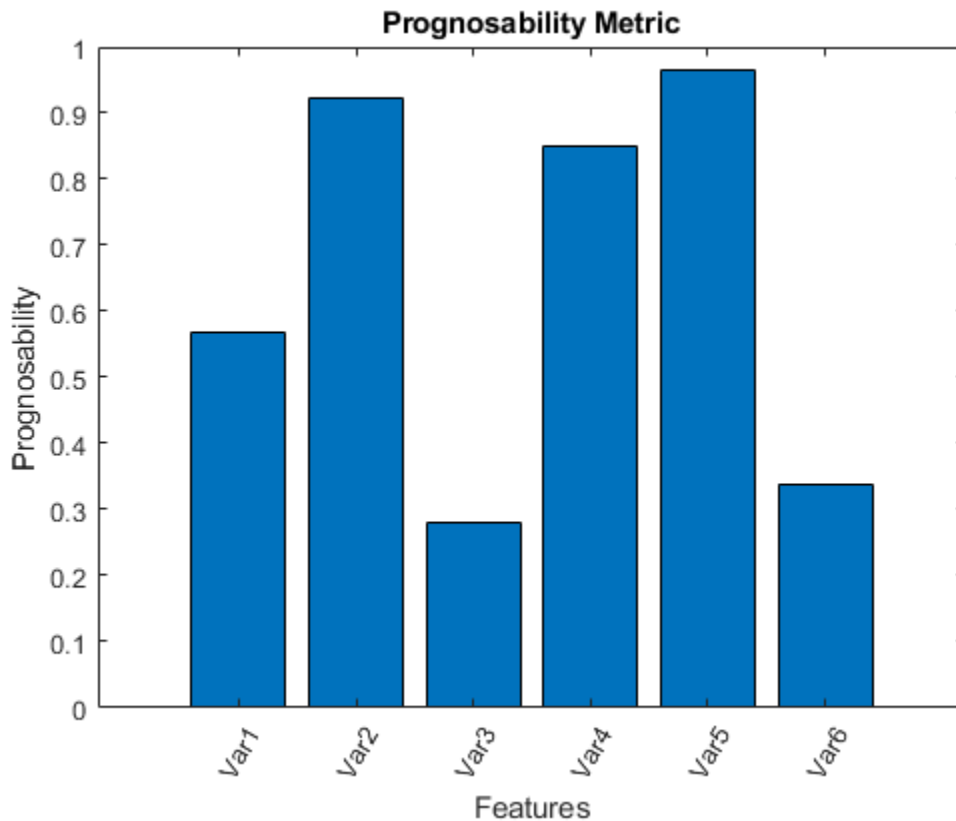




Observe the 6 different condition indicators—constant, linear, quadratic, cubic, logarithmic, and periodic—for all 10 machines on the plot.

Visualize the prognosability of the potential condition indicators.

`prognosability(C)`



From the histogram plot, observe that the features Var2, Var4 and Var5 rank better than the others. Hence, these features are more appropriate for remaining useful life predictions since they are the best indicators of machine health.

### **Prognosability of Data in Cell Array of Tables**

In this example, consider the lifetime data of 10 identical machines with the following 6 potential condition indicators—constant, linear, quadratic, cubic, logarithmic, and periodic. The data set `machineDataTable.mat` contains `T`, which is a 1x10 cell array of

tables where each element of the cell array contains a table of lifetime data for a machine.

Load and display the data.

```
load('machineDataTable.mat','T');
display(T)
```

```
T = 1x10 cell array
Columns 1 through 4
    {219x7 table}    {189x7 table}    {202x7 table}    {199x7 table}
Columns 5 through 8
    {229x7 table}    {184x7 table}    {224x7 table}    {208x7 table}
Columns 9 through 10
    {181x7 table}    {197x7 table}
```

```
head(T{1},2)
```

```
ans=2x7 table
    Time    Constant    Linear    Quadratic    Cubic    Logarithmic    Periodic
    _____    _____    _____    _____    _____    _____    _____
    0          3.2029    11.203    7.7029    3.8829    2.2517    0.2029
    0.05      2.8135    10.763    7.2637    3.6006    1.8579    0.12251
```

Note that every table in the cell array contains the lifetime variable 'Time' and the data variables 'Constant', 'Linear', 'Quadratic', 'Cubic', 'Logarithmic', and 'Periodic'.

Compute prognosability with Time as the lifetime variable.

```
Y = prognosability(T,'Time')
```

```
Y=1x6 table
    Constant    Linear    Quadratic    Cubic    Logarithmic    Periodic
    _____    _____    _____    _____    _____    _____
    0.56697    0.92321    0.28044    0.85048    0.96475    0.33853
```

From the resultant table of prognosability values, observe that the linear, cubic, and logarithmic features have values closer to 1. Hence, these three features are more appropriate for predicting remaining useful life since they are the best indicators of machine health.

## Visualize Prognosability of Lifetime Data in Ensemble Datastore

Consider the lifetime data of 4 machines. Each machine has 4 fault codes for the potential condition indicators—voltage, current, and power. `prognosabilityEnsemble.zip` is a collection of 4 files where every file contains a timetable of lifetime data for each machine - `tbl1.mat`, `tbl2.mat`, `tbl3.mat` and `tbl4.mat`. You can also use files containing data for multiple machines. For each timetable, the organization of the data is as follows:

Time	Voltage	Current	Power	FaultCode	Machine

Extract the compressed files, read the data in the timetables, and create a `fileEnsembleDatastore` object using the timetable data. For more information on creating a file ensemble datastore, see `fileEnsembleDatastore`.

```
unzip prognosabilityEnsemble.zip;
ens = fileEnsembleDatastore(pwd, '.mat');
ens.DataVariables = {'Voltage', 'Current', 'Power', 'FaultCode', 'Machine'};
% Make sure that the function for reading data is on path
addpath(fullfile(matlabroot, 'examples', 'predmaint', 'main'))
ens.ReadFcn = @readtable_data;
ens.SelectedVariables = {'Voltage', 'Current', 'Power', 'FaultCode', 'Machine'};
```

Visualize the prognosability of the potential condition indicators with 'Machine' as the member variable and group the lifetime data by 'FaultCode'. Grouping the lifetime data ensures that prognosability calculates the metric for each fault code separately.

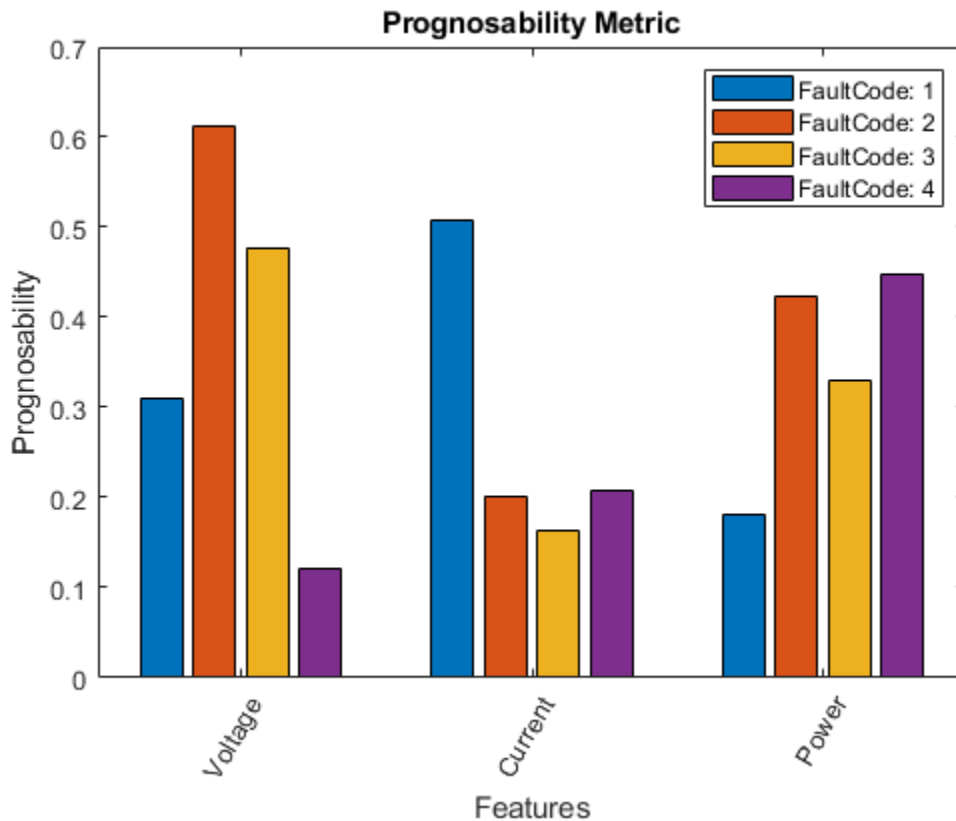
```
prognosability(ens, 'MemberVariable', 'Machine', 'GroupBy', 'FaultCode');
```

```
Starting parallel pool (parpool) using the 'local' profile ...
connected to 12 workers.
Evaluating tall expression using the Parallel Pool 'local':
- Pass 1 of 1: Completed in 8.3 sec
Evaluation completed in 14 sec
```

```

Evaluating tall expression using the Parallel Pool 'local':
- Pass 1 of 1: Completed in 13 sec
Evaluation completed in 14 sec
Evaluating tall expression using the Parallel Pool 'local':
- Pass 1 of 1: Completed in 3.5 sec
Evaluation completed in 3.6 sec

```



`prognosability` returns a histogram plot with the features ranked by their prognosability values. A higher prognosability value indicates a more suitable condition indicator. For instance, the candidate feature `Current` has the highest degree of prognosability for machines with `FaultCode 1`.

```
rmpath(fullfile(matlabroot, 'examples', 'predmaint', 'main')) % Reset path
```

## Input Arguments

### **X — Lifetime data**

cell array of matrices | cell array of tables and timetables | `fileEnsembleDatastore` object | table | timetable

Lifetime data, specified as a cell array of matrices, cell array of tables and timetables, `fileEnsembleDatastore` object, table, or timetable. Lifetime data contains run-to-failure data of the systems being monitored. The term *lifetime* here refers to the life of the machine defined in terms of the units you use to measure system life. Units of lifetime can be quantities such as the distance traveled (miles), fuel consumed (gallons), or time since the start of operation (days).

If X is

- a cell array of matrices or tables, the function assumes that each matrix or table contains columns of lifetime data for a system. Each column of every matrix or table, except the first column, contains data for a prognostic variable. `'Var1'`, `'Var2'`, ... can be used to refer to the matrix columns that contain the lifetime data. For instance, the file `machineDataCellArray.mat` contains a 1-by-10 cell array of matrices C, where each of the 10 matrices contains data for a particular machine.
- a table or timetable, the function assumes that each column, except the first one, contains columns of lifetime data. The table variable names can be used to refer to the columns that contain the lifetime data. If `lifetimeVar` is not specified when X is a table, then the first data column is used as the lifetime variable.
- a `fileEnsembleDatastore` object, specify the data variables `dataVar` and member variables `memberVar` to be used. If `lifetimeVar` is not specified, then the first data column is used as the lifetime variable for computation.

Each numerical member in X is of type `double`.

### **lifetimeVar — Lifetime variable**

string | character vector

Lifetime variable, specified as a string or character vector. `lifetimeVar` measures the lifetime of the systems being monitored and the lifetime data is sorted with respect to `lifetimeVar`. The value of `lifetimeVar` must be a valid ensemble or table variable name.

For a cell array of matrices, the value 'Time' can be used to refer to the first column of each matrix, which is assumed to contain the lifetime variable. For instance, the file `machineDataCellArray.mat` contains the cell array `C`, where the first column in each matrix contains the lifetime variable while the other columns contain the data variables.

### **dataVar — Data variables**

string array | character vector | cell array of character vectors

Data variables, specified as a string array, character vector, or cell array of character vectors. Data variables are the main content of the members of an ensemble. Data variables can include measured data or derived data for the analysis and development of predictive maintenance algorithms.

If `X` is

- a `fileEnsembleDatastore` object, the value of `dataVar` supersedes the `DataVariables` property of the ensemble.
- a cell array of matrices, the value 'Time' can be used to refer to the first column of each matrix, that is, the lifetime variable `lifetimeVar`. 'Var1', 'Var2', ... can be used to refer to the other matrix columns which contain the lifetime data. For instance, the file `machineDataCellArray.mat` contains the cell array `C` where the first column in each matrix contains the lifetime variable. The other columns in the cell array `C` contain the data variables.
- a table, the table variable names can be used to refer to the columns which contain the lifetime data.

The values of `dataVar` must be valid ensemble or table variable names. If `dataVar` is not specified, the computation includes all data columns except the one specified in `lifetimeVar`. For instance, suppose that each entry in a cell array is a table with variables `A`, `B`, `C`, and `D`. Setting `dataVar` to `["A", "D"]` uses only `A` and `D` for the computation while `C` and `D` are ignored.

### **memberVar — Member variable**

string | character vector

Member variable, specified as a string or character vector. Use `memberVar` to specify the variable for identifying the systems or machines in lifetime data `X`. For instance, in the `fileEnsembleDatastore` object, the fifth column in each timetable contains numbers that identify data from a particular machine. The column name corresponds to the member variable `memberVar`.

memberVar is ignored when X is specified as a cell array of matrices or tables.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of Name, Value arguments. Name is the argument name and Value is the corresponding value. Name must appear inside quotes. You can specify several name and value pair arguments in any order as Name1, Value1, ..., NameN, ValueN.

Example: ..., 'WindowSize', 0

### LifeTimeVariable — Lifetime variable

strings(0) (default) | string | character vector

Lifetime variable, specified as the comma-separated pair consisting of 'LifeTimeVariable' and either a string or character vector. If 'LifeTimeVariable' is not specified, then the first data column is used.

'LifeTimeVariable' is equivalent to the input argument lifetimeVar.

### DataVariables — Data variables

strings(0) (default) | string array | character vector | cell array of character vectors

Data variables, specified as the comma-separated pair consisting of 'DataVariables' and either a string array, character vector or cell array of character vectors.

'DataVariables' is equivalent to the input argument dataVar.

### MemberVariable — Member variables

[] (default) | string | character vector

Member variables, specified as the comma-separated pair consisting of 'MemberVariable' and either a string or character vector.

'MemberVariable' is equivalent to the input argument memberVar.

### GroupBy — Grouping criterion

[] (default) | string | character vector

Grouping criterion, specified as the comma-separated pair consisting of 'GroupBy' and either a string or character vector. Use 'GroupBy' to specify the variables for grouping the lifetime data X by operating conditions.



The function computes the metric separately for each group that results from applying the criterion, such as a fault condition, specified by 'GroupBy'. For instance, in the `fileEnsembleDatastore` object `ens`, the fourth column in each timetable in `ens` contains the variable 'FaultCode'. The metric is computed for each machine by grouping the data by 'FaultCode'.

You can only group variables when `X` is defined as a `fileEnsembleDatastore` object, table, timetable, or cell array of tables or timetables.

## Output Arguments

### **Y — Prognosability of lifetime data**

vector | table

Prognosability of lifetime data, returned as a vector or table.

Prognosability is the measure of the variability of a feature at failure based on the trajectories of the feature measured in several run-to-failure experiments. A more prognosable feature has less variation at failure relative to the range between its initial and final values. As a system gets progressively closer to failure, a suitable condition indicator is typically highly prognosable. Conversely, any feature that is non-prognosable is a less suitable condition indicator. The values of `Y` range from 0 to 1.

- `Y` is 1 if `X` is perfectly prognosable.
- `Y` is 0 if `X` is perfectly non-prognosable.

Selecting appropriate estimation parameters out of all available features is the first step in building a reliable remaining useful life prediction engine. The prognosability values in `Y` are useful to determine which condition indicators best track the degradation process of systems being monitored. The higher the prognosability, the more desirable the feature is for RUL prediction.

When 'GroupBy' is not specified, then `Y` is returned as a row vector or single-row table. Conversely, when 'GroupBy' is specified, then each row in `Y` corresponds to one group.

## Limitations

- When `X` is a tall table or tall timetable, `prognosability` nevertheless loads the complete array into memory using `gather`. If the memory available is inadequate, then `prognosability` returns an error.

## Algorithms

The computation of `prognosability` uses this formula:

$$prognosability = \exp\left(-\frac{std_j(x_j(N_j))}{mean_j(|x_j(1) - x_j(N_j)|)}\right), \quad j = 1, \dots, M$$

where  $x_j$  represents the vector of measurements of a feature on the  $j^{th}$  system, variable  $M$  is the number of systems monitored, and  $N_j$  is the number of measurements on the  $j^{th}$  system.

## References

- [1] Coble, J., and J. W. Hines. "Identifying Optimal Prognostic Parameters from Data: A Genetic Algorithms Approach." In *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. 2009.
- [2] Coble, J. "Merging Data Sources to Predict Remaining Useful Life - An Automated Method to Identify Prognostics Parameters." Ph.D. Thesis. University of Tennessee, Knoxville, TN, 2010.
- [3] Lei, Y. *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Xi'an, China: Xi'an Jiaotong University Press, 2017.
- [4] Lofti, S., J. B. Ali, E. Bechhoefer, and M. Benbouzid. "Wind turbine high-speed shaft bearings health prognosis through a spectral Kurtosis-derived indices and SVR." *Applied Acoustics* Vol. 120, 2017, pp. 1-8.

## See Also

`fileEnsembleDatastore` | `monotonicity` | `trendability`

**Introduced in R2018b**

## read

Read member data from an ensemble datastore

Use this function to read data from ensemble datastores for condition monitoring and predictive maintenance.

## Syntax

```
data = read(ensemble)
[data,info] = read(ensemble)
```

## Description

`data = read(ensemble)` reads data from a member of the ensemble datastore `ensemble`. The function reads the variables specified in the `SelectedVariables` property of the ensemble datastore and returns them in a table.

If the ensemble has not been read since its creation (or since it was last reset using `reset`), then `read` reads data from the first member of the ensemble, as determined by the software. Otherwise, `read` reads data from the next ensemble member. `read` updates the `LastMemberRead` property of the ensemble to identify the most recently read member. For more information about how ensemble datastores work, see “Data Ensembles for Condition Monitoring and Predictive Maintenance”.

`[data,info] = read(ensemble)` also returns information about the location from which the data is read and the size of the data.

## Examples

### Extract Subset of Stored Variables from Ensemble Member

In general, you use the `read` command to extract data from a `simulationEnsembleDatastore` object into the MATLAB® workspace. Often, your

ensemble contains more variables than you need to use for a particular analysis. Use the `SelectedVariables` property of the `simulationEnsembleDatastore` object to select a subset of variables for reading.

For this example, use the following code to create a `simulationEnsembleDatastore` object using data previously generated by running a Simulink® model at a various fault values (See `generateSimulationEnsemble`). The ensemble includes simulation data for five different values of a model parameter, `ToothFaultGain`. Because of the volume of data, the `unzip` operation takes a few minutes.

```
unzip simEnsData.zip % extract compressed files
ensemble = simulationEnsembleDatastore(pwd, 'logout')
```

```
ensemble =
    simulationEnsembleDatastore with properties:
```

```
    DataVariables: [5x1 string]
IndependentVariables: [0x0 string]
ConditionVariables: [0x0 string]
SelectedVariables: [5x1 string]
    ReadSize: 1
    NumMembers: 5
    LastMemberRead: [0x0 string]
    Files: [5x1 string]
```

The model that generated the data, `TransmissionCasingSimplified`, was configured such that the resulting ensemble contains variables including accelerometer data, `Vibration`, and tachometer data, `Tacho`. By default, the `simulationEnsembleDatastore` object designates all these variables as both data variables and selected variables, as shown in the `DataVariables` and `SelectedVariables` properties.

```
ensemble.DataVariables
```

```
ans = 5x1 string array
    "PMSignalLogName"
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
```

```
ensemble.SelectedVariables
```

```
ans = 5x1 string array
    "PMSignalLogName"
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
```

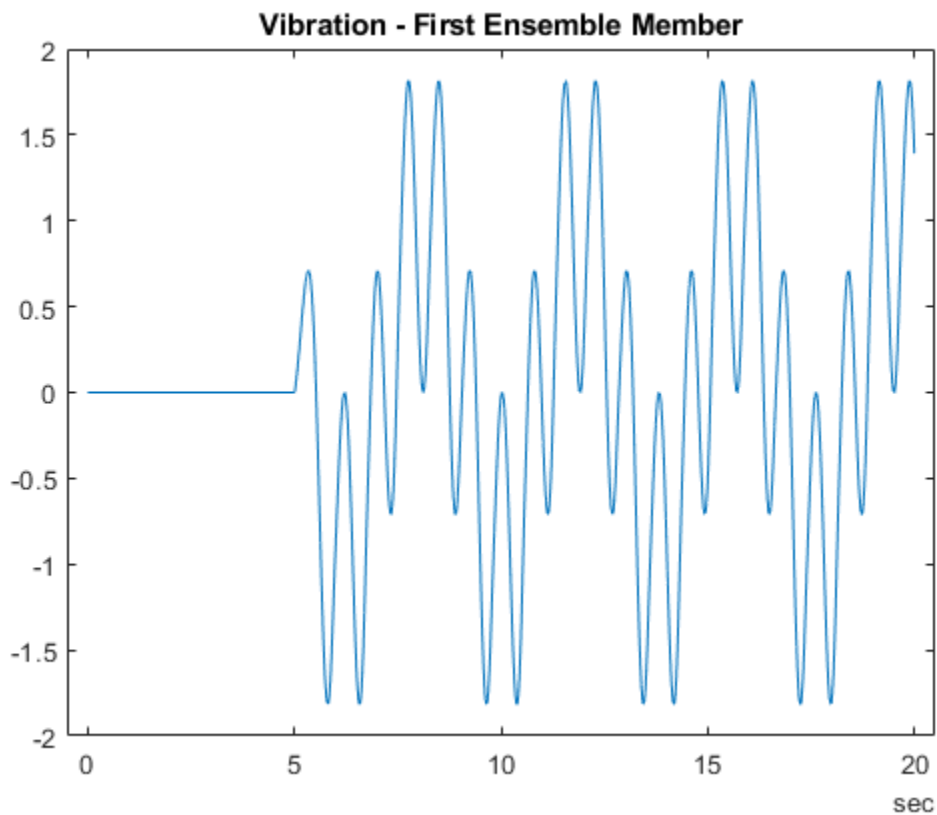
Suppose that for the analysis you want to do, you need only the `Vibration` data and the `Simulink.SimulationInput` object that describes the conditions under which this member data was simulated. Set `ensemble.SelectedVariables` to specify the variables you want to read. The `read` command then extracts those variables from the current ensemble member.

```
ensemble.SelectedVariables = ["Vibration";"SimulationInput"];
data1 = read(ensemble)
```

```
data1=1x2 table
      Vibration      SimulationInput
      _____      _____
      [20202x1 timetable]  [1x1 Simulink.SimulationInput]
```

`data.Vibration` is a cell array containing one `timetable` that stores the simulation times and the corresponding vibration signal. You can now process this data as needed. For instance, extract the vibration data from the table and plot it.

```
vibdata1 = data1.Vibration{1};
plot(vibdata1.Time,vibdata1.Data)
title('Vibration - First Ensemble Member')
```



The next time you call `read` on this ensemble, the last-read member designation advances to the next member of the ensemble (see “Data Ensembles for Condition Monitoring and Predictive Maintenance”). Read the selected variables from the next member of the ensemble.

```
data2 = read(ensemble)
```

```
data2=1x2 table
```

```
Vibration
```

```
SimulationInput
```

```
[20215x1 timetable]
```

```
[1x1 Simulink.SimulationInput]
```

To confirm that `data1` and `data2` contain data from different ensemble members, examine the values of the varied model parameter, `ToothFaultGain`. For each ensemble, this value is stored in the `Variables` field of the `SimulationInput` variable.

```
data1.SimulationInput{1}.Variables
```

```
ans =  
  Variable with properties:  
  
      Name: 'ToothFaultGain'  
      Value: -2  
  Workspace: 'global-workspace'
```

```
data2.SimulationInput{1}.Variables
```

```
ans =  
  Variable with properties:  
  
      Name: 'ToothFaultGain'  
      Value: -1.5000  
  Workspace: 'global-workspace'
```

This result confirms that `data1` is from the ensemble member with `ToothFaultGain` = -2, and `data2` is from the member with `ToothFaultGain` = -1.5.

### Read from and Write to a File Ensemble Datastore

Create a file ensemble datastore for data stored in MATLAB files, and configure it with functions that tell the software how to read from and write to the datastore. (For more details about configuring file ensemble datastores, see “File Ensemble Datastore With Measured Data”.) Because of the volume of data, the unzip operation takes a few minutes.

```
% Create ensemble datastore that points to datafiles in current folder  
unzip fileEnsData.zip % extract compressed files  
location = pwd;  
extension = '.mat';  
fensemble = fileEnsembleDatastore(location,extension);  
  
% Specify data and condition variables
```



```
fensemble.DataVariables = ["gs";"sr";"load";"rate"];
fensemble.ConditionVariables = "label";
```

```
% Configure with functions for reading and writing variable data
addpath(fullfile(matlabroot,'examples','predmaint','main')) % Make sure functions are c
fensemble.ReadFcn = @readBearingData;
fensemble.WriteToMemberFcn = @writeBearingData;
```

The functions tell the `read` and `writeToLastMemberRead` commands how to interact with the data files that make up the ensemble. Thus, when you call the `read` command, it uses `readBearingData` to read all the variables in `fensemble.SelectedVariables`. For this example, `readBearingData` extracts requested variables from a structure, `bearing`, and other variables stored in the file. It also parses the filename for the fault status of the data.

Specify variables to read, and read them from the first member of the ensemble.

```
fensemble.SelectedVariables = ["gs";"load";"label"];
data = read(fensemble)
```

```
data=1x3 table
      label          gs          load
      _____  _____  _____
      "Faulty"    [146484x1 double]    0
```

You can now process the data from the member as needed. For this example, compute the average value of the signal stored in the variable `gs`. Extract the data from the table returned by `read`.

```
gsdata = data.gs{1};
gsmean = mean(gsdata);
```

You can write the mean value `gsmean` back to the data file as a new variable. To do so, first expand the list of data variables in the ensemble to include a variable for the new value. Call the new variable `gsMean`.

```
fensemble.DataVariables = [fensemble.DataVariables;"gsMean"]
```

```
fensemble =
  fileEnsembleDatastore with properties:
      ReadFcn: @readBearingData
```

```
WriteToMemberFcn: @writeBearingData
  DataVariables: [5x1 string]
IndependentVariables: [0x0 string]
ConditionVariables: "label"
SelectedVariables: [3x1 string]
  ReadSize: 1
  NumMembers: 5
LastMemberRead: "C:\TEMP\Bdoc18b_943130_7372\ib632619\14\tpf2dcb597\predmain
  Files: [5x1 string]
```

Next, write the derived mean value to the file corresponding to the last-read ensemble member. (See “Data Ensembles for Condition Monitoring and Predictive Maintenance”.) When you call `writeToLastMemberRead`, it converts the data to a structure and calls `fensemble.WriteToMemberFcn` to write the data to the file.

```
writeToLastMemberRead(fensemble, 'gsMean', gsmean);
```

Calling `read` again advances the last-read-member indicator to the next file in the ensemble and reads the data from that file.

```
data = read(fensemble)
```

```
data=1x3 table
  label          gs          load
  -----
  "Faulty"      [146484x1 double]      50
```

You can confirm that this data is from a different member by examining the `load` variable in the table. Here, its value is 50, while in the previously read member, it was 0.

You can repeat the processing steps to compute and append the mean for this ensemble member. In practice, it is more useful to automate the process of reading, processing, and writing data. To do so, reset the ensemble to a state in which no data has been read. Then loop through the ensemble and perform the read, process, and write steps for each member.

```
reset(fensemble)
while hasdata(fensemble)
  data = read(fensemble);
  gsdata = data.gs{1};
  gsmean = mean(gsdata);
```

```

        writeToLastMemberRead(fensemble, 'gsMean', gsmean);
end

```

The `hasdata` command returns `false` when every member of the ensemble has been read. Now, each data file in the ensemble includes the `gsMean` variable derived from the data `gs` in that file. You can use techniques like this loop to extract and process data from your ensemble files as you develop a predictive-maintenance algorithm. For an example illustrating in more detail the use of a file ensemble datastore in the algorithm-development process, see “Rolling Element Bearing Fault Diagnosis”. The example also shows how to use Parallel Computing Toolbox™ to speed up the processing of large data ensembles.

To confirm that the derived variable is present in the file ensemble datastore, read it from the first and second ensemble members. To do so, reset the ensemble again, and add the new variable to the selected variables. In practice, after you have computed derived values, it can be useful to read only those values without rereading the unprocessed data, which can take significant space in memory. For this example, read selected variables that include the new variable, `gsMean`, but do not include the unprocessed data, `gs`.

```

reset(fensemble)
fensemble.SelectedVariables = ["label"; "load"; "gsMean"];
data1 = read(fensemble)

```

```

data1=1×3 table
    label    load    gsMean
    -----
    "Faulty"    0    -0.23

```

```

data2 = read(fensemble)

```

```

data2=1×3 table
    label    load    gsMean
    -----
    "Faulty"    50    -0.22352

```

```

rmpath(fullfile(matlabroot, 'examples', 'predmaint', 'main')) % Reset path

```

## Read Multiple Ensemble Members in One Operation

To read data from multiple ensemble members in one call to the `read` command, use the `ReadSize` property of an ensemble datastore. This example uses `simulationEnsembleDatastore`, but you can use the same technique for `fileEnsembleDatastore`.

Use the following code to create a `simulationEnsembleDatastore` object using data previously generated by running a Simulink model at a various fault values (see `generateSimulationEnsemble`). The ensemble includes simulation data for five different values of a model parameter, `ToothFaultGain`. (Because of the volume of data, the unzip operation might take a minute or two.) Specify some of the data variables to read.

```
unzip simEnsData.zip % extract compressed files
ensemble = simulationEnsembleDatastore(pwd, 'logout');
ensemble.SelectedVariables = ["Vibration"; "SimulationInput"];
```

By default, calling `read` on this ensemble datastore returns a single-row table containing the values of the `Vibration` and `SimulationInput` variables for the first ensemble member. Change the `ReadSize` property to read three members at once.

```
ensemble.ReadSize = 3;
data1 = read(ensemble)
```

```
data1=3x2 table
           Vibration           SimulationInput
-----
[20202x1 timetable] [1x1 Simulink.SimulationInput]
[20215x1 timetable] [1x1 Simulink.SimulationInput]
[20204x1 timetable] [1x1 Simulink.SimulationInput]
```

`read` returns a three-row table, where each row contains data from one of the first, second, and third ensemble members. `read` also updates the `LastReadMember` property of the ensemble datastore to a string array containing the paths of the three corresponding files. Avoid setting `ReadSize` to a value so large as to risk running out of memory while loading the data.

If the ensemble contains three or more additional members, the next `read` operation returns data from the fourth, fifth, and sixth members. Because the ensemble of this example contains only five members total, the next `read` operation returns only two rows.

```
data2 = read(ensemble)
```

```
data2=2x2 table
      Vibration      SimulationInput
-----
 [20213x1 timetable] [1x1 Simulink.SimulationInput]
 [20224x1 timetable] [1x1 Simulink.SimulationInput]
```

## Input Arguments

### **ensemble** — Ensemble datastore

fileEnsembleDatastore object | simulationEnsembleDatastore object

Ensemble datastore to read, specified as a:

- `simulationEnsembleDatastore` object — `read` reads the next ensemble member.
- `fileEnsembleDatastore` object — `read` uses the function specified in the `ensemble.ReadFcn` property to read the next ensemble member. (For more information about working with file ensemble datastores, see `fileEnsembleDatastore`.)

In either case, `read` returns a table containing all the variables specified in `ensemble.SelectedVariables`.

## Output Arguments

### **data** — Selected variables from ensemble member

table

Selected variables from the ensemble member, returned as a `table`. The table variables are the selected variables, and the table data are the values read from the ensemble data. By default, `read` reads one ensemble member at a time and returns a single table row.

To read multiple ensemble members at one time, set the `ReadSize` property of `ensemble` to a value greater than 1. For instance, if you set `ReadSize` to 3, then `read` reads the next 3 ensemble members and returns a table with 3 rows. If fewer than `ReadSize`

members are unread, then `read` returns a table with as many rows as there are remaining members. For an example, see “Read Multiple Ensemble Members in One Operation” on page 1-111. Avoid setting `ReadSize` to such a large value as to risk running out of memory while loading data.

### **info — Data and member information**

structure

Data and ensemble member information, returned as a structure with fields:

- `Size` — Dimensions of the table `data`, returned as a vector. For instance, if your ensemble has four variables specified in `ensemble.SelectedVariables`, then `Info.Size = [1 4]`.
- `FileName` — Path to the data file corresponding to the accessed ensemble member, returned as a string. For example, “C:\Data\Experiment1\fault1.mat”. Calling `read` also sets the `LastMemberRead` property of the ensemble to this value. If the `ReadSize` property of `ensemble` is greater than 1, this value is a string vector containing the paths to all the accessed files.

## **See Also**

`fileEnsembleDatastore` | `simulationEnsembleDatastore`

## **Topics**

“Data Ensembles for Condition Monitoring and Predictive Maintenance”

**Introduced in R2018a**

# restart

Reset remaining useful life degradation model

## Syntax

```
restart mdl  
restart mdl, resetPrior  
restart( ____, Name, Value)
```

## Description

`restart(mdl)` resets the internally stored statistics of the degradation process accumulated by the previous calls to `update` and resets the `InitialLifeTimeValue` and `CurrentLifeTimeValue` properties of the model. If the `SlopeDetectionLevel` property of the model is not empty, then the slope test is also restarted, ignoring any previous detections.

`restart(mdl, resetPrior)` sets the prior parameter values in `mdl` to their corresponding posterior values when `resetPrior` is `true`.

`restart( ____, Name, Value)` specifies properties of `mdl` using one or more name-value pair arguments.

## Examples

### Reset Degradation Model

Load training data, which is a degradation feature profile for a component.

```
load('expRealTime.mat')
```

For this example, assume that the training data is not historical data. When there is no historical data, you can update your degradation model in real time using observed data.

Create an exponential degradation model with the following settings:

- $\theta$  prior distribution with a mean of 2.4 and a variance of 0.006
- $\beta$  prior distribution with a mean of 0.07 and a variance of 3e-5
- Noise variance of 0.003

```
mdl = exponentialDegradationModel('Theta',2.4,'ThetaVariance',0.006,...  
                                'Beta',0.07,'BetaVariance',3e-5,...  
                                'NoiseVariance',0.003);
```

Since there is no life time variable in the training data, create an arbitrary life time vector for fitting.

```
lifeTime = [1:length(expRealTime)];
```

Observe the degradation feature for 100 iterations. Update the degradation model after each iteration.

```
for i=1:100  
    update(mdl,[lifeTime(i) expRealTime(i)])  
end
```

Reset the model, which clears the accumulated statistics from the previous observations and resets the posterior distributions to the prior distributions.

```
restart(mdl)
```

### **Update Exponential Degradation Model in Real Time**

Load training data, which is a degradation feature profile for a component.

```
load('expRealTime.mat')
```

For this example, assume that the training data is not historical data. When there is no historical data, you can update your degradation model in real time using observed data.

Create an exponential degradation model with the following settings:

- Arbitrary  $\theta$  and  $\beta$  prior distributions with large variances so that the model relies mostly on observed data



- Noise variance of 0.003

```
mdl = exponentialDegradationModel('Theta',1,'ThetaVariance',1e6,...
                                   'Beta',1,'BetaVariance',1e6,...
                                   'NoiseVariance',0.003);
```

Since there is no life time variable in the training data, create an arbitrary life time vector for fitting.

```
lifeTime = [1:length(expRealTime)];
```

Observe the degradation feature for 10 iterations. Update the degradation model after each iteration.

```
for i=1:10
    update(mdl,[lifeTime(i) expRealTime(i)])
end
```

After observing the model for some time, for example at a steady-state operating point, you can restart the model and save the current posterior distribution as a prior distribution.

```
restart(mdl,true)
```

View the updated prior distribution parameters.

```
mdl.Prior
ans = struct with fields:
    Theta: 2.3555
    ThetaVariance: 0.0058
    Beta: 0.0722
    BetaVariance: 3.6362e-05
    Rho: -0.8429
```

## Input Arguments

### mdl — Degradation RUL model

linearDegradationModel object | exponentialDegradationModel object

Degradation RUL model, specified as a linearDegradationModel object or an exponentialDegradationModel object. restart clears the accumulated statistics in

`mdl` and resets the `InitialLifeTimeValue` and `CurrentLifeTimeValue` properties of `mdl`.

## **resetPrior — Flag for resetting prior parameter values**

`false` (default) | `true`

Flag for resetting prior parameter information, specified as a logical value. When `resetPrior` is:

- `true`, then `restart` sets the prior parameter values of `mdl` to their corresponding current posterior parameter values. For example, `mdl.Prior.Theta` is set to `mdl.Theta`.
- `false` or omitted, then `restart` does not update the prior.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, . . . , NameN, ValueN`.

Example: `nv1, 'value'`

## **Theta — Mean value of model $\theta$ parameter**

scalar

This property is read-only.

Mean value of model  $\theta$  parameter, specified as the comma-separated pair `'Theta'` and a scalar. Use this argument to set the `Theta` property of `mdl` and the corresponding field of the `Prior` property of `mdl`.

## **ThetaVariance — Variance of model $\theta$ parameter**

nonnegative scalar

This property is read-only.

Variance of the  $\theta$  parameter in the degradation model, specified as the comma-separated pair `'ThetaVariance'` and a nonnegative scalar. Use this argument to set the `ThetaVariance` property of `mdl` and the corresponding field of the `Prior` property of `mdl`.

**Beta — Mean value of model  $\beta$  parameter**

scalar

This property is read-only.

Mean value of model  $\beta$  parameter, specified as the comma-separated pair 'Beta' and a scalar. Use this argument to set the Beta property of mdl and the corresponding field of the Prior property of mdl.

This argument applies only when mdl is an exponentialDegradationModel.

**BetaVariance — Variance of model  $\beta$  parameter**

nonnegative scalar

This property is read-only.

Variance of model  $\beta$  parameter, specified as the comma-separated pair 'BetaVariance' and a nonnegative scalar. Use this argument to set the BetaVariance property of mdl and the corresponding field of the Prior property of mdl.

This argument applies only when mdl is an exponentialDegradationModel.

**Rho — Correlation between  $\theta$  and  $\beta$** 

scalar value in the range [-1,1]

This property is read-only.

Correlation between  $\theta$  and  $\beta$ , specified as the comma-separated pair 'Rho' and a scalar value in the range [-1,1]. Use this argument to set the Rho property of mdl and the corresponding field of the Prior property of mdl.

This argument applies only when mdl is an exponentialDegradationModel.

**NoiseVariance — Model additive noise variance**

nonnegative scalar

Model additive noise variance, specified as the comma-separated pair 'NoiseVariance' and a nonnegative scalar. Use this argument to set the NoiseVariance property of mdl.

**SlopeDetectionLevel — Slope detection level**

scalar value in the range [0,1] | []

Slope detection level for determining the start of the degradation process, specified as the comma-separated pair 'SlopeDetectionLevel' and a scalar in the range [0,1]. Use this argument to set the `SlopeDetectionLevel` property of `mdl`.

To disable the slope detection test, set `SlopeDetectionLevel` to `[]`.

### **UseParallel — Flag for using parallel computing**

`false` (default) | `true`

Flag for using parallel computing when fitting prior values from data, specified as the comma-separated pair 'UseParallel' and either `true` or `false`. Use this argument to set the `UseParallel` property of `mdl`.

## **See Also**

### **Functions**

`exponentialDegradationModel` | `linearDegradationModel` | `update`

### **Topics**

"Models for Predicting Remaining Useful Life"

**Introduced in R2018a**

# tfmoment

Joint moment of the time-frequency distribution of a signal

Time-frequency moments provide an efficient way to characterize signals whose frequencies change in time (that is, are nonstationary). Such signals can arise from machinery with degraded or failed hardware. Classical Fourier analysis cannot capture the time-varying frequency behavior. Time-frequency distribution generated by short-time Fourier transform (STFT) or other time-frequency analysis techniques can capture the time-varying behavior, but directly treating these distributions as features carries a high computational burden, and potentially introduces unrelated and undesirable feature characteristics. In contrast, distilling the time-frequency distribution results into low-dimension time-frequency moments provides a method for capturing the essential features of the signal in a much smaller data package. Using these moments significantly reduces the computational burden for feature extraction and comparison — a key benefit for real-time operation [1], [2].

The Predictive Maintenance Toolbox™ implements the three branches of time-frequency moment:

- Conditional spectral moment — `tfsmoment`
- Conditional temporal moment — `tftmoment`
- Joint time-frequency moment — `tfmoment`

## Syntax

```
momentJ = tfmoment(xt,order)
momentJ = tfmoment(x,fs,order)
momentJ = tfmoment(x,ts,order)
momentJ = tfmoment(p,fp,tp,order)
momentJ = tfmoment( ____,Name,Value)
```

## Description

`momentJ = tfmoment(xt,order)` returns the “Joint Time-Frequency Moments” on page 1-129 of timetable `xt` as a vector with one or more components. Each `momentJ`

scalar element represents the joint moment for one of the orders you specify in `order`. The data in `xt` can be nonuniformly sampled.

`momentJ = tfmoment(x, fs, order)` returns the joint time-frequency moment of time-series vector `x`, sampled at rate `fs`. The moment is returned as a vector, in which each scalar element represents the joint moment corresponding to one of the orders you specify in `order`. With this syntax, `x` must be uniformly sampled.

`momentJ = tfmoment(x, ts, order)` returns the joint time-frequency moment of `x` sampled at the time instants specified by `ts` in seconds.

- If `ts` is a scalar duration, then `tfmoment` applies it uniformly to all samples.
- If `ts` is a vector, then `tfmoment` applies each element to the corresponding sample in `x`. Use this syntax for nonuniform sampling.

`momentJ = tfmoment(p, fp, tp, order)` returns the joint time-frequency moment of a signal whose power spectrogram is `p`. `fp` contains the frequencies corresponding to the spectral estimate contained in `p`. `tp` contains the vector of time instants corresponding to the centers of the windowed segments used to compute short-time power spectrum estimates. Use this syntax when:

- You already have the power spectrogram you want to use.
- You want to customize the options for `pspectrum`, rather than accept the default `pspectrum` options that `tfmoment` applies. Use `pspectrum` first with the options you want, and then use the output `p` as input for `tfmoment`. This approach also allows you to plot the power spectrogram.

`momentJ = tfmoment( ____, Name, Value)` specifies additional properties using name-value pair arguments. Options include moment centralization, frequency-limit specification, and time-limit specification.

You can use `Name, Value` with any of the input-argument combinations in previous syntaxes.

## Examples

## Find the Joint Time-Frequency Moments of a Time Series

Find the joint time-frequency moments of a time series using multiple moment specifications. Compute the same moment using a specified power spectrogram input.

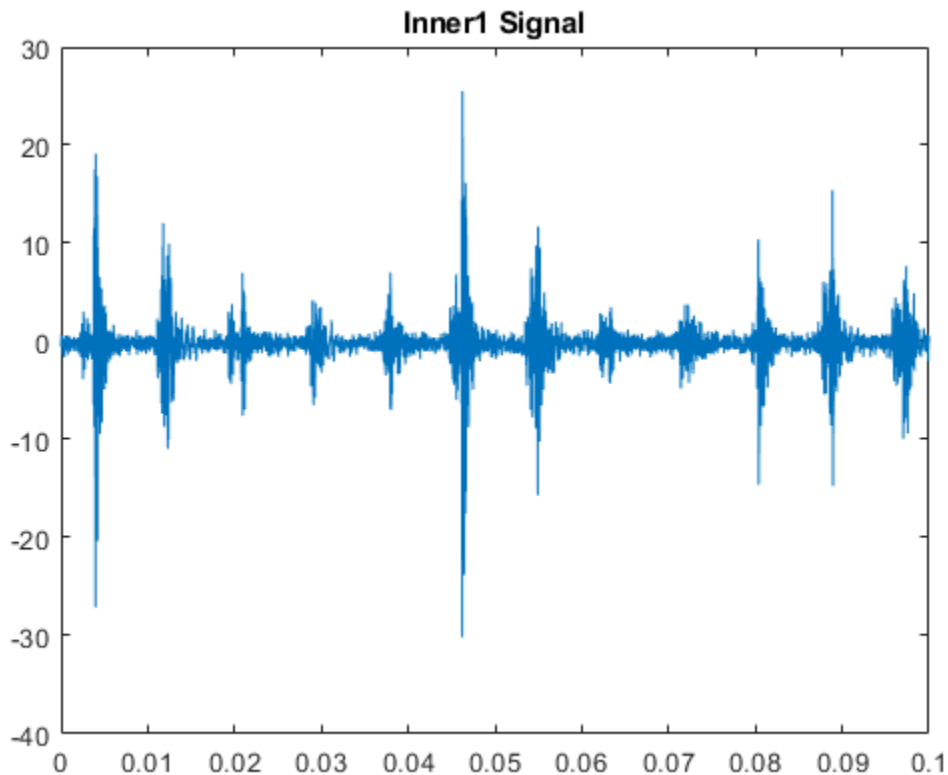
This example is adapted from “Rolling Element Bearing Fault Diagnosis”, which provides a more comprehensive treatment of the data sources and history.

Load the data, which contains vibration measurements for a faulty machine. `x_inner1` and `sr_inner1` contain the data vector and sample rate.

```
load tfmoment_data.mat x_inner1 sr_inner1
```

Examine the data. Construct a time vector from the sample rate, and plot the data. Then zoom in to an 0.1 s section so that the behavior can be seen more clearly.

```
t_inner1 = (0:length(x_inner1)-1)/sr_inner1; % Construct time vector of [0 1/sr 2/sr .  
figure  
plot(t_inner1,x_inner1)  
title ('Inner1 Signal')  
hold on  
xlim([0 0.1]) % Zoom in to an 0.1 s section  
hold off
```



The plot shows periodic impulsive variations in the acceleration measurements over time.

Find the joint moment of second order for both time and frequency

```
order = [2,2];  
momentJ = tfmoment(x_inner1,sr_inner1,order)  
  
momentJ = 3.6261e+08
```

The resulting moment has only one element, representing the [2,2] time-frequency pair.

Now include the fourth moment for time and frequency. You can also mix orders within a pair. Include a joint moment with a second order for time and a fourth order for frequency. The order matrix contains two columns — the first for time and the second for frequency. Each row contains the order pair to compute.



```

order = [2,2;2,4;4,4];
momentJ = tfmoment(x_inner1,t_inner1,order);
momentJ(1)

ans = 3.6261e+08

momentJ(2)

ans = 7.9513e+16

momentJ(3)

ans = 4.0896e+17

```

You can also take the moment using an existing spectrogram. Load the data for a spectrogram which was computed using the same signal and default options. Input this to `tfmoment`, using the 3-row order matrix already computed.

```

load tfmoment_data.mat p_inner1_def f_p_def t_p_def
momentJ = tfmoment(p_inner1_def,f_p_def,t_p_def,order);
momentJ(1)

ans = 3.6261e+08

momentJ(2)

ans = 7.9513e+16

momentJ(3)

ans = 4.0896e+17

```

The joint moments distill a large amount of time and frequency data into a small set of single data points. They represent important, and concise, features that you can use in multiple ways in your application. Possibilities include comparison with health-regime limits and computing moments of segmented data over a period of time to assess long-term degradation.

## Input Arguments

### **xt** — Time-series signal

timetable

Time-series signal for which `tfmoment` returns the moments, specified as a `timetable` that contains a single variable with a single column. `xt` must contain increasing, finite

row times. If the timetable has missing or duplicate time points, you can fix it using the tips in “Clean Timetable with Missing, Duplicate, or Nonuniform Times” (MATLAB). `xt` can be nonuniformly sampled, with the `pspectrum` constraint that the median time interval and the mean time interval must obey:

$$\frac{1}{100} < \frac{\text{Median time interval}}{\text{Mean time interval}} < 100.$$

**order — Moment orders to return**

positive integer matrix

Moment orders to return, specified as an n-by-2 matrix with real positive integers.

- The first column provides the orders of time.
- The second column provides the orders of frequency.

Example: `momentJ = tfmoment(x, [2,2])` specifies the second-order joint moment (variance) of the time-frequency distribution of `x`.

Example: `momentJ = tfmoment(x, [2,2;4,4])` specifies the second and fourth moment orders for both time and frequency of the time-frequency distribution of `x`.

You can specify any order and number of orders, but low-order moments carry less computational burden and are better suited to real-time applications. You can also use a different order for time than you use for frequency. The first four moment orders correspond to the statistical moments of a data set:

- 1 Mean
- 2 Variance
- 3 Skewness (degree of asymmetry about the mean)
- 4 Kurtosis (length of outlier tails in the distribution — a normal distribution has a kurtosis of 3)

For an example, see “Find the Joint Time-Frequency Moments of a Time Series” on page 1-122.

**x — Time-series signal**

vector

Time-series signal from which `tfmoment` returns the moments, specified as a vector.

For an example of a time-series input, see “Find the Joint Time-Frequency Moments of a Time Series” on page 1-122.

### **fs — Sample rate**

positive scalar

Sample rate of  $x$ , specified as positive scalar in hertz when  $x$  is uniformly sampled.

### **ts — Sample-time values**

duration scalar | vector | duration vector | datetime vector

Sample-time values, specified as one of the following:

- duration scalar — time interval between consecutive samples of  $X$ .
- Vector, duration array, or datetime array — time instant or duration corresponding to each element of  $x$ .

$ts$  can be nonuniform, with the `pspectrum` constraint that the median time interval and the mean time interval must obey:

$$\frac{1}{100} < \frac{\text{Median time interval}}{\text{Mean time interval}} < 100.$$

### **p — Power spectrogram or spectrum of signal**

matrix | vector

Power spectrogram or spectrum of a signal, specified as a matrix (spectrogram) or a column vector (spectrum).  $p$  contains an estimate of the short-term, time-localized power spectrum of a time-series signal. If you specify  $p$ , then `tfmoment` uses  $p$  rather than generate its own power spectrogram. For an example, see “Find the Joint Time-Frequency Moments of a Time Series” on page 1-122.

### **fp — Frequencies for p**

vector

Frequencies for power spectrogram or spectrum  $p$  when  $p$  is supplied explicitly to `tfmoment`, specified as a vector in hertz. The length of  $fp$  must be equal to the number of rows in  $p$ .

### **tp — Time information for p**

vector | duration vector | datetime vector | duration scalar

Time information for power spectrogram or spectrum `p` when `p` is supplied explicitly to `tfmoment`, specified as one of the following:

- Vector of time points, whose data type can be numeric, `duration`, or `datetime`. The length of vector `tp` must be equal to the number of columns in `p`.
- `duration` scalar that represents the time interval in `p`. The scalar form of `tp` can be used only when `p` is a power spectrogram matrix.
- For the special case where `p` is a column vector (power spectrum), `tp` can be a numeric, `duration`, or `datetime` scalar representing the time point of the spectrum.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, . . . , NameN, ValueN`.

Example: `'Centralize', false, 'FrequencyLimits', [10 100]` computes the joint time-frequency moment for the portion of the signal ranging from 10 Hz to 100 Hz.

### **Centralize** — Centralize-moment option

`true` (default) | `false`

Centralize-moment option, specified as the comma-separated pair consisting of `'Centralize'` and a logical.

- If `Centralize` is `true`, then `tfmoment` returns the centralized conditional moment by subtracting the conditional mean (which is the first moment) in the computation.
- If `Centralize` is `false`, then `tfmoment` returns the noncentralized moment, preserving any data offset.

Example: `momentJ = tfmoment(x, [2,2], 'Centralize', false)`.

### **FrequencyLimits** — Frequency limits

full frequency band (default) | [`f1` `f2`]

Frequency limits to use, specified as the comma-separated pair consisting of `'FrequencyLimits'` and a two-element vector containing lower and upper bounds `f1` and `f2` in hertz. This specification allows you to exclude a band of data at either end of the spectral range.

**TimeLimits — Time Limits**

full time band (default) | [t1 t2]

Time limits, specified as the comma-separated pair consisting of 'TimeLimits' and a two-element vector containing lower and upper bounds t1 and t2 in the same units as ts, and of the data types:

- Numeric or duration when fs or a scalar ts are specified, or when ts is a single, double, or duration vector
- Numeric, duration, or datetime when ts is specified as a datetime vector

This specification allows you to extract a temporal section of data from a longer data set.

## Output Arguments

**momentJ — Conditional joint moment**

vector

Conditional joint moment returned as a vector, the scalar elements of which each represents the joint moment of one of the specified time-frequency order pairs.

momentJ is always a vector, regardless of whether the input data is timetable xt, time-series vector x, or spectrogram data p.

## Definitions

### Joint Time-Frequency Moments

The joint time-frequency moments of a nonstationary signal comprise a set of time-varying parameters that characterize the signal spectrum as it evolves in time. They are related to the conditional temporal moments and the joint time-frequency moments. The joint time-frequency moment is an integral function of frequency, given time, and marginal distribution. The conditional temporal moment is an integral function of time, given frequency, and marginal distribution. The calculation of the joint time-frequency moment is a double integral that varies both time and frequency [1], [2].

Each moment is associated with a specific order, with the first four orders being the statistical properties of 1) mean, 2) variance, 3) skewness, and 4) kurtosis.

`tfmoment` computes the joint time-frequency moments of the time-frequency distribution for a signal  $x$ , for the orders specified in `order`. The function performs these steps:

- 1 Compute the spectrogram power spectrum,  $P(t,f)$ , of the input using the `pspectrum` function and uses it as a time-frequency distribution. If the syntax used supplies an existing  $P(t,f)$ , then `tfmoment` uses that instead.

- 2 Estimate the joint time-frequency moment  $\langle t^n \omega^m \rangle$  of the signal using, for the noncentralized case:

$$\langle t^n \omega^m \rangle = \iint t^n \omega^m P(t, \omega) dt d\omega,$$

where  $m$  is the order and  $P(t)$  is the marginal distribution.

For the centralized joint time-frequency moment  $\mu_{t,\omega}^{n,m}(t)$ , the function uses

$$\mu_{t,\omega}^{n,m}(t) = \frac{1}{P(\omega)} \iint \left( t - \langle t^1 \rangle_{\omega} \right)^n \left( \omega - \langle \omega^1 \rangle_t \right)^m P(t, \omega) dt d\omega,$$

where  $\langle t^1 \rangle_{\omega}$  and  $\langle \omega^1 \rangle_t$  are the first temporal and spectral time-frequency moments.

## References

- [1] Loughlin, P. J. "What Are the Time-Frequency Moments of a Signal?" *Advanced Signal Processing Algorithms, Architectures, and Implementations XI, SPIE Proceedings*. Vol. 4474, November 2001.
- [2] Loughlin, P, F. Cakrak, and L. Cohen. "Conditional Moment Analysis of Transients with Application to Helicopter Fault Data." *Mechanical Systems and Signal Processing*. Vol 14, Issue 4, 2000, pp. 511-522.

## See Also

`pspectrum` | `tfsmoment` | `tftmoment`

**Introduced in R2018a**

## **tfsmoment**

Conditional spectral moment of the time-frequency distribution of a signal

Time-frequency moments provide an efficient way to characterize signals whose frequencies change in time (that is, are nonstationary). Such signals can arise from machinery with degraded or failed hardware. Classical Fourier analysis cannot capture the time-varying frequency behavior. Time-frequency distribution generated by short-time Fourier transform (STFT) or other time-frequency analysis techniques can capture the time-varying behavior, but directly treating these distributions as features carries a high computational burden, and potentially introduces unrelated and undesirable feature characteristics. In contrast, distilling the time-frequency distribution results into low-dimension time-frequency moments provides a method for capturing the essential features of the signal in a much smaller data package. Using these moments significantly reduces the computational burden for feature extraction and comparison — a key benefit for real-time operation [1], [2].

The Predictive Maintenance Toolbox implements the three branches of time-frequency moment:

- Conditional spectral moment — `tfsmoment`
- Conditional temporal moment — `tftmoment`
- Joint time-frequency moment — `tfmoment`

## **Syntax**

```
momentS = tfsmoment(xt,order)
momentS = tfsmoment(x,fs,order)
momentS = tfsmoment(x,ts,order)
momentS = tfsmoment(p,fp,tp,order)
momentS = tfsmoment( ____,Name,Value)
```

```
[momentS,t] = tfsmoment( ____)
```

```
tfsmoment( ____)
```



## Description

`momentS = tfsmoment(xt,order)` returns the conditional spectral moment on page 1-155 of timetable `xt` as a timetable. The `momentS` variables provide the spectral moments for the orders you specify in `order`. The data in `xt` can be nonuniformly sampled.

`momentS = tfsmoment(x,fs,order)` returns the conditional spectral moment of time-series vector `x`, sampled at rate `Fs`. The moment is returned as a matrix, in which each column represents a spectral moment corresponding each element in `order`. With this syntax, `x` must be uniformly sampled.

`momentS = tfsmoment(x,ts,order)` returns the conditional spectral moment of `x` sampled at the time instants specified by `ts` in seconds.

- If `ts` is a scalar duration, then `tfsmoment` applies it uniformly to all samples.
- If `ts` is a vector, then `tfsmoment` applies each element to the corresponding sample in `x`. Use this syntax for nonuniform sampling.

`momentS = tfsmoment(p,fp,tp,order)` returns the conditional spectral moment of a signal whose power spectrogram is `p`. `fp` contains the frequencies corresponding to the spectral estimate contained in `p`. `tp` contains the vector of time instants corresponding to the centers of the windowed segments used to compute short-time power spectrum estimates. Use this syntax when:

- You already have the power spectrum or spectrogram you want to use.
- You want to customize the options for `pspectrum`, rather than accept the default `pspectrum` options that `tfsmoment` applies. Use `pspectrum` first with the options you want, and then use the output `p` as input for `tfsmoment`. This approach also allows you to plot the power spectrogram.

`momentS = tfsmoment( ____,Name,Value)` specifies additional properties using name-value pair arguments. Options include moment centralization and frequency-limit specification.

You can use `Name,Value` with any of the input-argument combinations in previous syntaxes.

`[momentS,t] = tfsmoment( ____ )` returns time vector `t`.

You can use `t` with any of the input-argument combinations in previous syntaxes.

`tfsmoment( ___ )` with no output arguments plots the conditional spectral moment. The plot x-axis is time, and the plot y-axis is the corresponding spectral moment.

You can use this syntax with any of the input-argument combinations in previous syntaxes.

## Examples

### Plot the Conditional Spectral Moment of a Time Series Vector

Plot the second-order conditional spectral moment (variance) of a time series using the plot-only approach and the return-data approach. Visualize the moment differently by plotting the histogram. Compare the moments for data arising from faulty and healthy machine conditions.

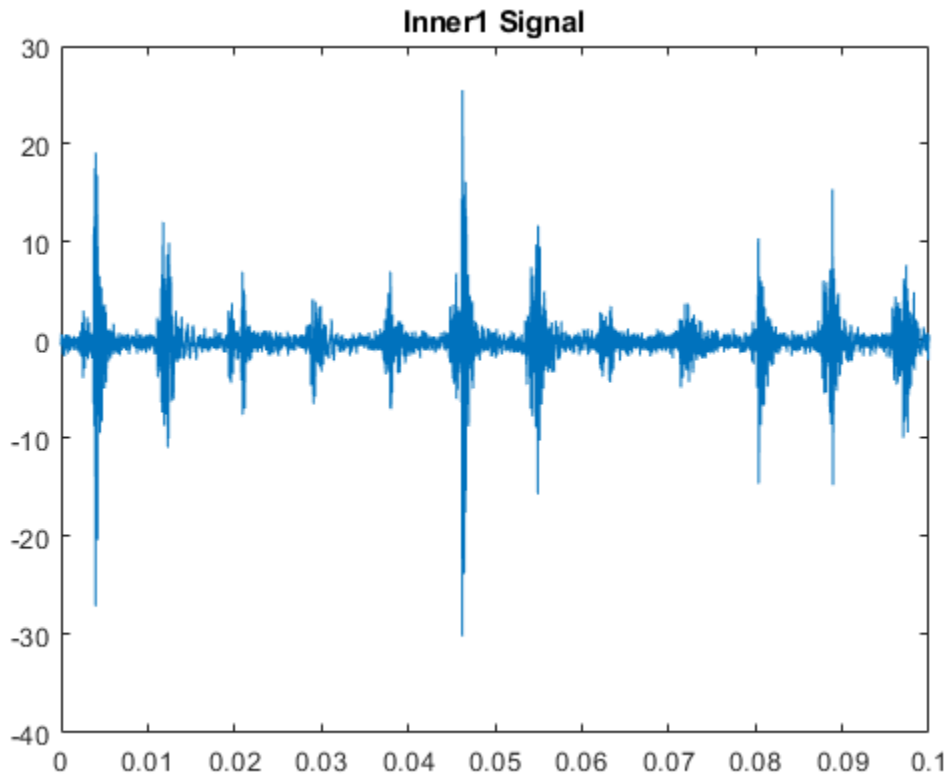
This example is adapted from “Rolling Element Bearing Fault Diagnosis”, which provides a more comprehensive treatment of the data sources and history.

Load the data, which contains vibration measurements for two conditions. `x_inner1` and `sr_inner1` contain the data vector and sample rate for a faulty condition. `x_baseline` and `sr_baseline` contain the data vector and sample rate for a healthy condition.

```
load tfmoment_data.mat x_inner1 sr_inner1 x_baseline1 sr_baseline1
```

Examine the faulty-condition data. Construct a time vector from the sample rate, and plot the data. Then zoom in to an 0.1-s section so that the behavior can be seen more clearly.

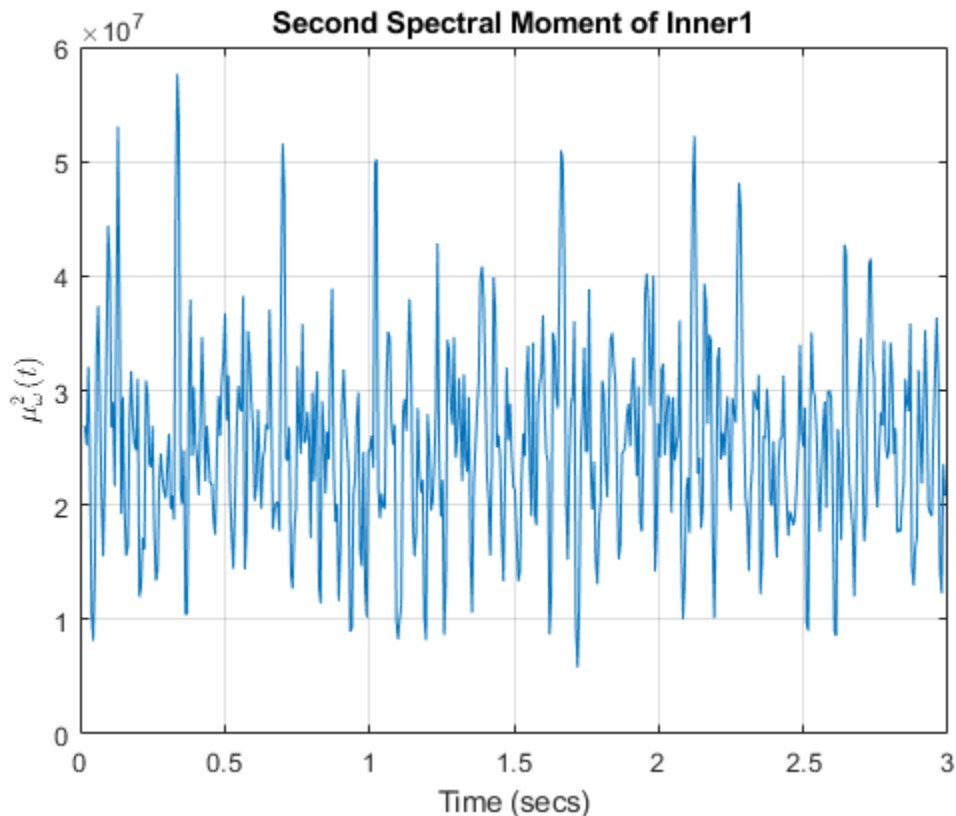
```
t_inner1 = (0:length(x_inner1)-1)/sr_inner1; % Construct time vector of [0 1/sr 2/sr . . .]
figure
plot(t_inner1,x_inner1)
title('Inner1 Signal')
hold on
xlim([0 0.1]) % Zoom in to an 0.1 s section
hold off
```



The plot shows periodic impulsive variations in the acceleration measurements over time.

Plot the second spectral moment (order=2), using the `tfsmoment` syntax with no output arguments.

```
order = 2;  
figure  
tfsmoment(x_inner1,t_inner1,order)  
title('Second Spectral Moment of Inner1')
```

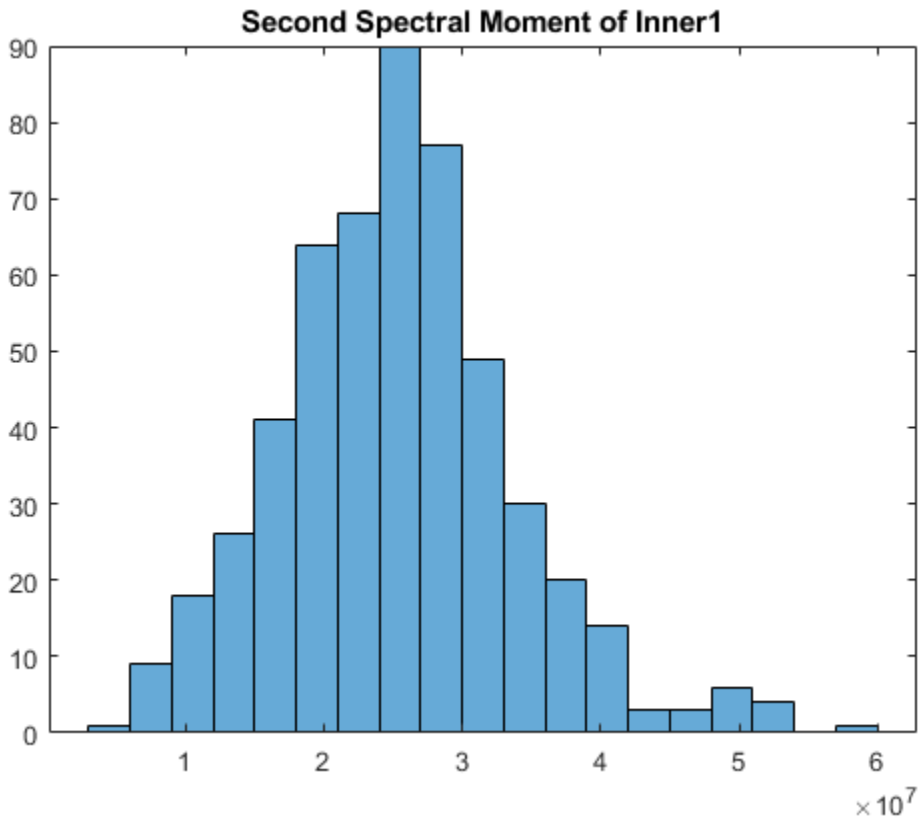


The plot illustrates the changes in the variance of the `x_inner1` spectrum over time. You are limited to this visualization (moment versus time) because `tfsmoment` returned no data. Now use `tfsmoment` again to compute the second spectral moment, this time using the syntax that returns both the moment values and the associated time vector. You can use the sample rate directly in the syntax (`sr_inner1`), rather than the time vector you constructed (`t_inner1`).

```
[momentS_inner1,t1_inner1] = tfsmoment(x_inner1,sr_inner1,order);
```

You can now plot moment versus time as you did before, using `moment_inner1` and `t1_inner1`, with the same result as earlier. But you can also perform additional analysis and visualization of the moment vector, since `tfsmoment` returned the data. A histogram can provide concise information on the signal characteristics.

```
figure
histogram(momentS_inner1)
title('Second Spectral Moment of Inner1')
```



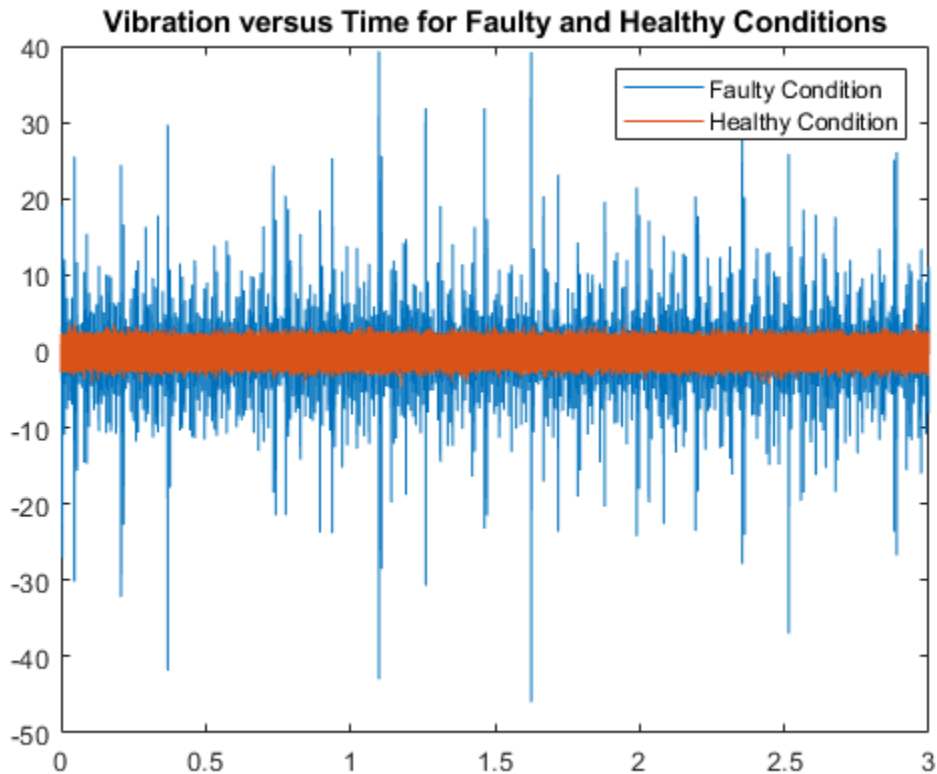
On its own, the histogram does not reveal obvious fault information. However, you can compare it to the histogram produced by the healthy-condition data.

First, compare the inner and baseline time series directly using the same time-vector construction for the `baseline1` data as previously for the `inner1` data.

```
t_baseline1 = (0:length(x_baseline1)-1)/sr_baseline1;
```

```
figure
plot(t_inner1,x_inner1)
```

```
hold on
plot(t_baseline1,x_baseline1)
hold off
legend('Faulty Condition','Healthy Condition')
title('Vibration versus Time for Faulty and Healthy Conditions')
```

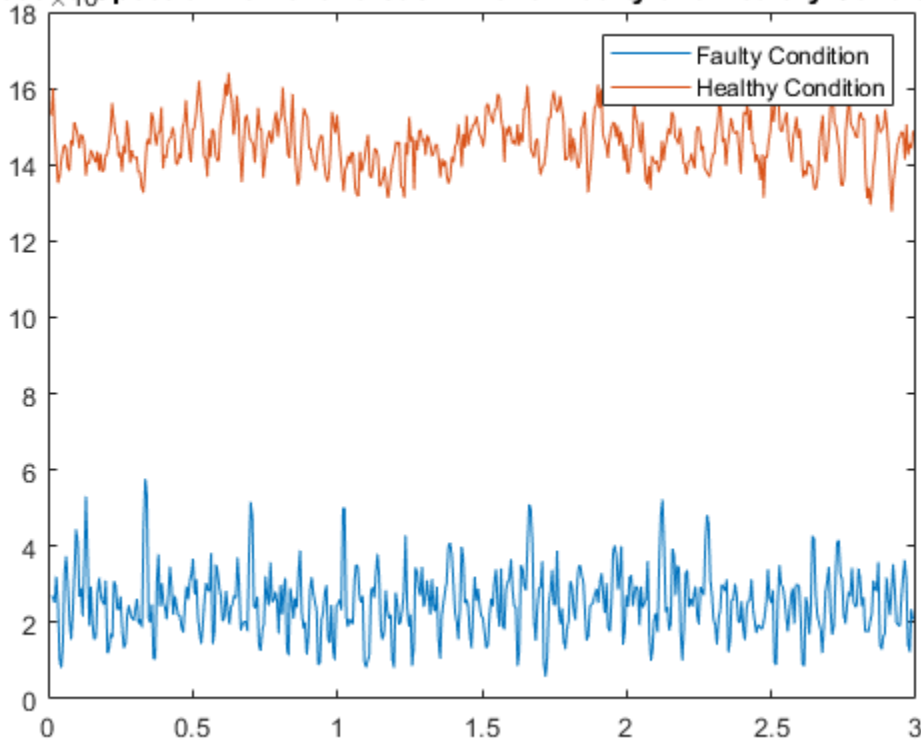


Calculate the second spectral moment of the `baseline1` data. Compare the `baseline1` and `inner1` time histories.

```
[momentS_baseline1,t1_baseline1] = tfsmoment(x_baseline1,sr_baseline1,2);
figure
plot(t1_inner1,momentS_inner1)
hold on
```

```
plot(t1_baseline1,momentS_baseline1)
hold off
legend('Faulty Condition','Healthy Condition')
title('Second Spectral Moment versus Time for Faulty and Healthy Conditions')
```

**Second Spectral Moment versus Time for Faulty and Healthy Conditions**



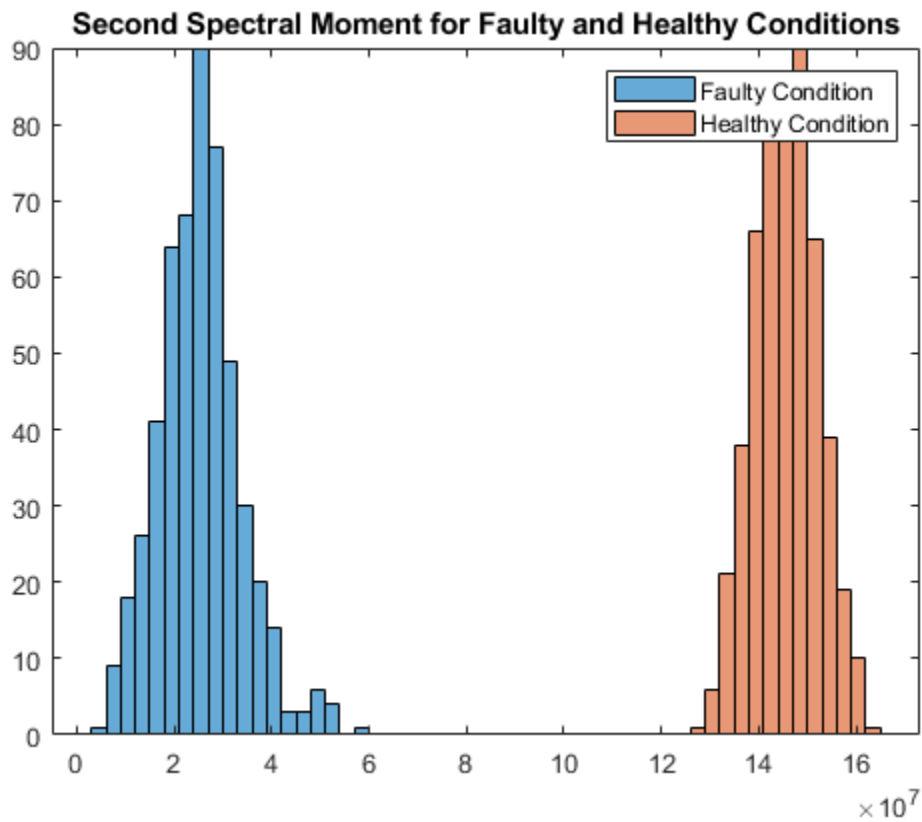
The moment plot shows behavior different from the earlier vibration plot. The vibration data for the faulty case is much noisier with higher-magnitude spikes than for the healthy case, although both appear to be zero mean. However, the spectral variance (second spectral moment) is significantly lower for the faulty case. The moment of the faulty case is still more noisy than the healthy case.

Plot the histograms.

```

figure
histogram(momentsS_inner1);
hold on
histogram(momentsS_baseline1);
hold off
legend('Faulty Condition', 'Healthy Condition')
title('Second Spectral Moment for Faulty and Healthy Conditions')

```



The moment behaviors distinguish the faulty condition from the healthy condition in both plots. The histogram provides distinct distribution characteristics — center point along x-axis, spread, and peak histogram bin.



## Determine Multiple Orders of Conditional Spectral Moment for a Time Series

Determine the first four conditional spectral moments of a time-series data set, and extract the moments that you want to visualize with a histogram.

Load the data, which contains vibration measurements (`x_inner1`) and sample rate (`sr_inner1`) for machinery. Then use `tfsmoment` to compute the first four moments. These moments represent the statistical quantities of: 1) Mean; 2) Variance; 3) Skewness; and 4) Kurtosis.

You can specify the moment designators as a vector within the order argument.

```
load tfsmoment_data.mat x_inner1 sr_inner1
momentS_inner1 = tfsmoment(x_inner1,sr_inner1,[1 2 3 4]);
```

Compare the dimensions of the input vector and the output matrix.

```
xsize = size(x_inner1)
```

```
xsize = 1x2
```

```
146484    1
```

```
msize = size(momentS_inner1)
```

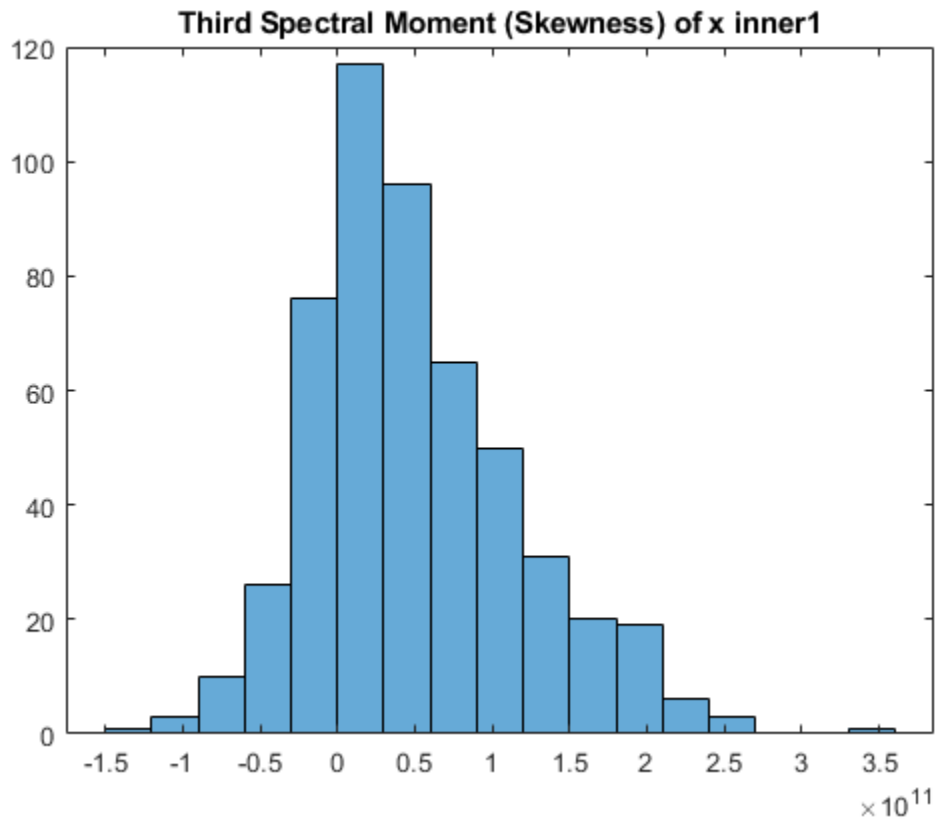
```
msize = 1x2
```

```
524    4
```

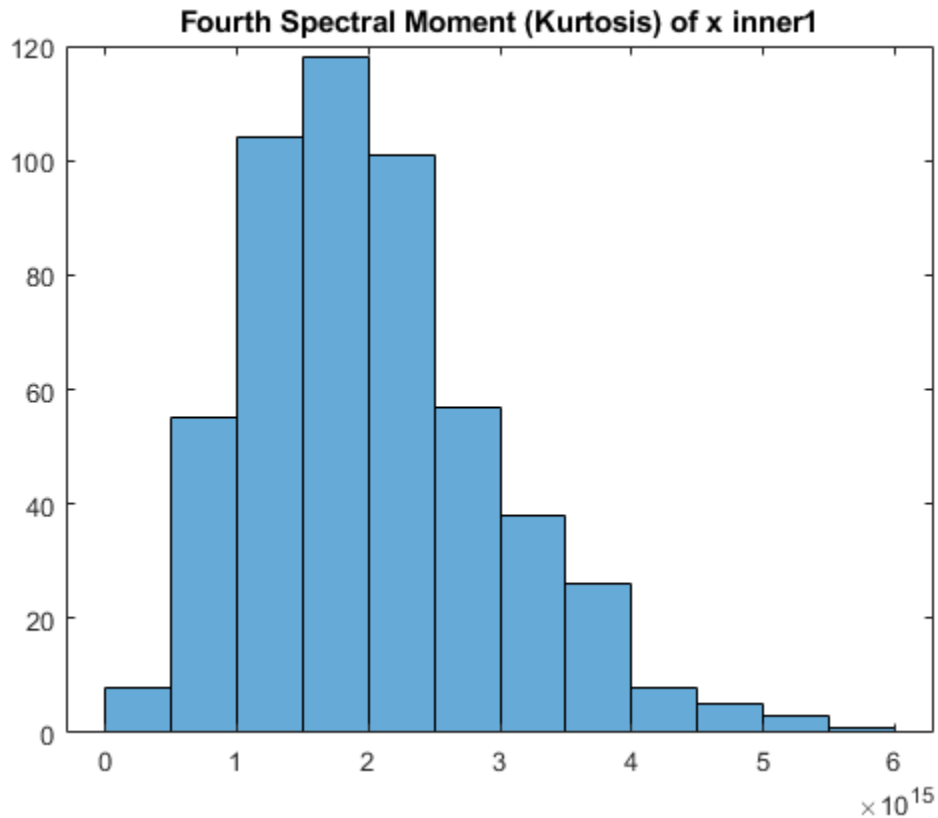
The data vector `x_inner` is considerably longer than the vectors in the moment matrix `momentS_inner1` because the spectrogram computation produces optimally-sized lower-resolution time windows. In this case, `tfsmoment` returns a moment matrix containing four columns, one column for each moment order.

Plot the histograms for the third (skewness) and fourth (kurtosis) moments. The third and fourth columns of `momentS_inner1` provide these.

```
momentS_3 = momentS_inner1(:,3);
momentS_4 = momentS_inner1(:,4);
figure
histogram(momentS_3)
title('Third Spectral Moment (Skewness) of x_inner1')
```



```
figure
histogram(moments_4)
title('Fourth Spectral Moment (Kurtosis) of x inner1')
```



The plots are similar, but each has some unique characteristics with respect to number of bins and slope steepness.

### **Use a Customized Power Spectrogram to Compute the Conditional Spectral Moment**

By default, `tfsmoment` calls the function `pspectrum` internally to generate the power spectrogram that `tfsmoment` uses for the moment computation. You can also import an existing power spectrogram for `tfsmoment` to use instead. This capability is useful if you already have a power spectrogram as a starting point, or if you want to customize the `pspectrum` options by generating the spectrogram explicitly first.

Input a power spectrogram that has been generated with customized options. Compare the resulting spectral-moment histogram with one that `tfsmoment` generates using its `pspectrum` default options.

Load the data, which includes two power spectrums and the associated frequency and time vectors.

The `p_inner1_def` spectrum was created using the default `pspectrum` options. It is equivalent to what `tfsmoment` computes internally when an input spectrum is not provided in the syntax.

The `p_inner1_MinThr` spectrum was created using the `MinThreshold` `pspectrum` option. This option puts a lower bound on nonzero values to screen out low-level noise. For this example, the threshold was set to screen out noise below the 0.5% level.

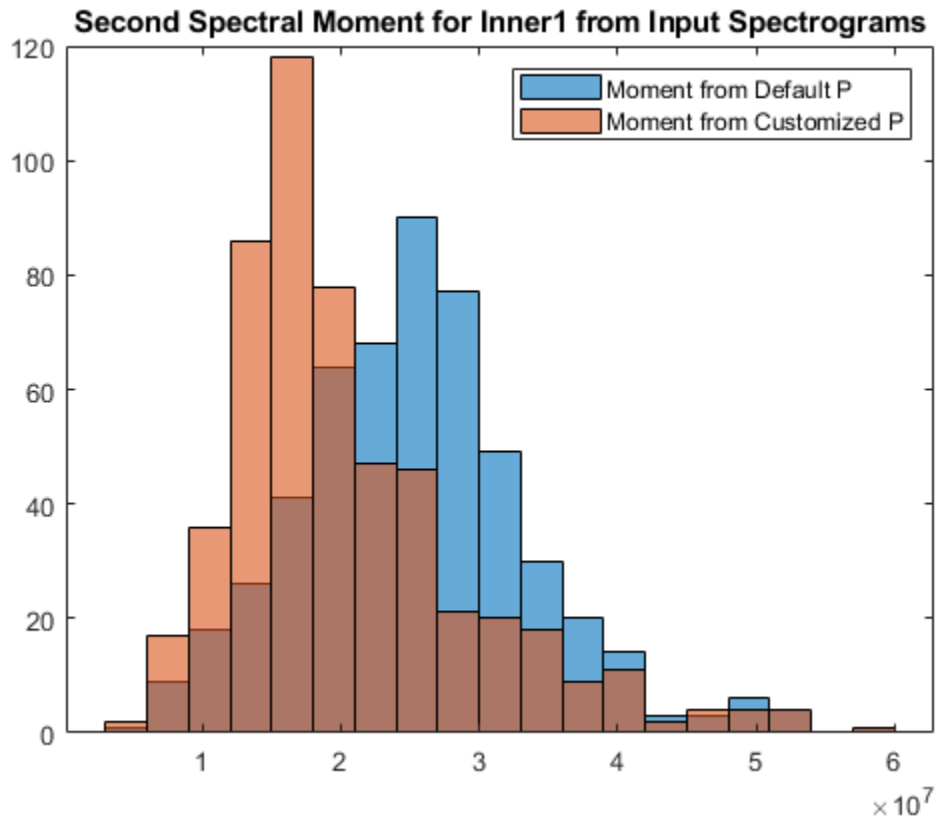
```
load tfmoment_data.mat p_inner1_def f_p_def t_p_def ...
    p_inner1_MinThr f_p_MinThr t_p_MinThr
load tfmoment_data.mat x_inner1 x_baseline1
```

Determine the second spectral moments (variance) for both cases.

```
moment_p_def = tfsmoment(p_inner1_def,f_p_def,t_p_def,2);
moment_p_MinThr = tfsmoment(p_inner1_MinThr,f_p_MinThr,t_p_MinThr,2);
```

Plot the histograms together.

```
figure
histogram(moment_p_def);
hold on
histogram(moment_p_MinThr);
hold off
legend('Moment from Default P','Moment from Customized P')
title('Second Spectral Moment for Inner1 from Input Spectrograms')
```



The histograms have the same overall spread, but the thresholded moment histogram has a higher peak bin at a lower moment magnitude level than the default moment. This example is for illustration purposes only, but does show the impact that preprocessing in the spectrum computation stage can have.

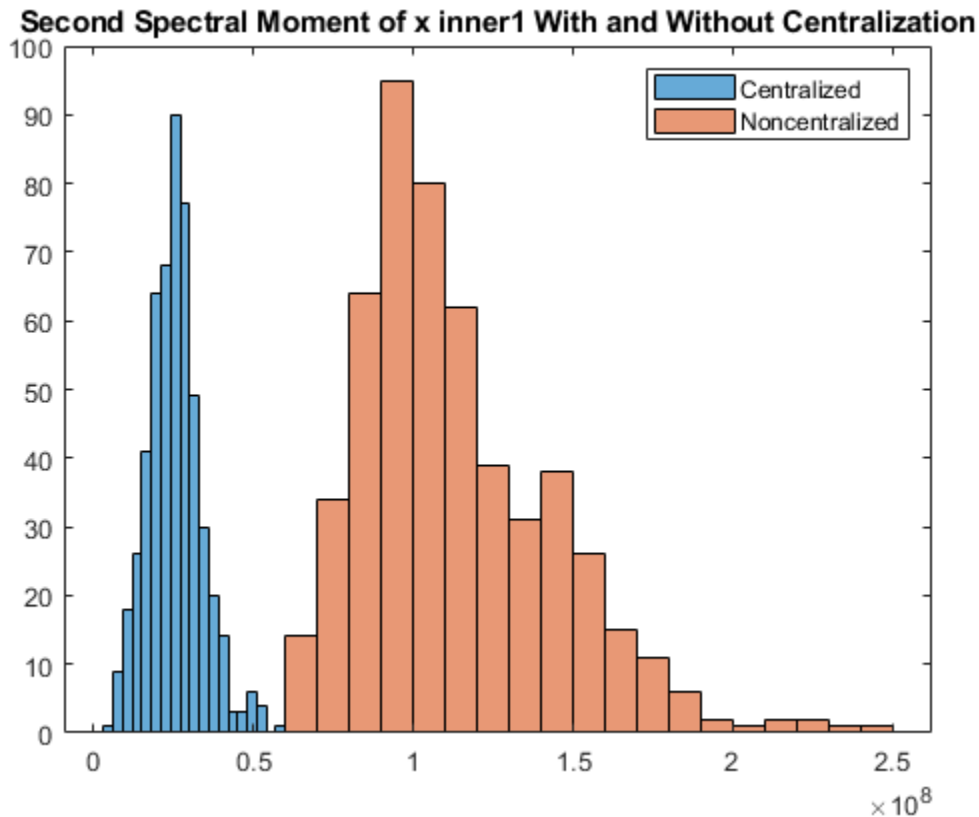
### Calculate a Conditional Spectral Moment that is not Centralized

By default, `tfsmoment` centralizes the moment as part of its calculation. That is, it subtracts the sensor-data mean (which is the first moment) from the sensor data as part of the “Conditional Spectral Moments” on page 1-155. If you wish to preserve the offset, you can set the input argument `Centralize` to `false`.

Load the data, which contains vibration measurements `x` and sample rate `sr` for machinery. Calculate the 2nd moment (`order = 2`) both with centralization (default), and without centralization (`Centralize = false`). Plot the histograms together.

```
load tfmoment_data.mat x_inner1 sr_inner1
momentS_centr = tfsmoment(x_inner1,sr_inner1,2);
momentS_nocentr = tfsmoment(x_inner1,sr_inner1,2,'Centralize',false);

figure
histogram(momentS_centr)
hold on
histogram(momentS_nocentr);
hold off
legend('Centralized','Noncentralized')
title('Second Spectral Moment of x_inner1 With and Without Centralization')
```



The noncentralized distribution is offset to the right.

### Find the Conditional Spectral Moments of Data Measurements in a Timetable

Real-world measurements often come packaged as part of a time-stamped table that records actual time and readings rather than relative times. You can use the `timetable` format for capturing this data. This example shows how `tfsmoment` operates with a `timetable` input, in contrast to the data vector inputs used for the other `tfsmoment` examples, such as “Plot the Conditional Spectral Moment of a Time Series Vector” on page 1-134.

Load the data, which consists of a single timetable `xt_inner1` containing measurement readings and time information for a piece of machinery. Examine the properties of the timetable.

```
load tfmoment_tdata.mat xt_inner1;
xt_inner1.Properties
```

```
ans =
    TimetableProperties with properties:

        Description: ''
        UserData: []
        DimensionNames: {'Time' 'Variables'}
        VariableNames: {'x_inner1'}
    VariableDescriptions: {}
        VariableUnits: {}
    VariableContinuity: []
        RowTimes: [146484x1 duration]
        StartTime: 0 sec
        SampleRate: 4.8828e+04
        TimeStep: 2.048e-05 sec
    CustomProperties: No custom properties are set.
    Use addprop and rmprop to modify CustomProperties.
```

This table consists of dimensions `Time` and the `Variables`, where the only variable is `x_inner1`.

Find the second and fourth conditional spectral moments for the data in the timetable. Examine the properties of the resulting moment timetable.

```
order = [2 4];
momentS_xt_inner1 = tfsmoment(xt_inner1,order);
momentS_xt_inner1.Properties
```

```
ans =
    TimetableProperties with properties:

        Description: ''
        UserData: []
        DimensionNames: {'Time' 'Variables'}
        VariableNames: {'CentralSpectralMoment2' 'CentralSpectralMoment4'}
    VariableDescriptions: {}
        VariableUnits: {}
    VariableContinuity: []
```



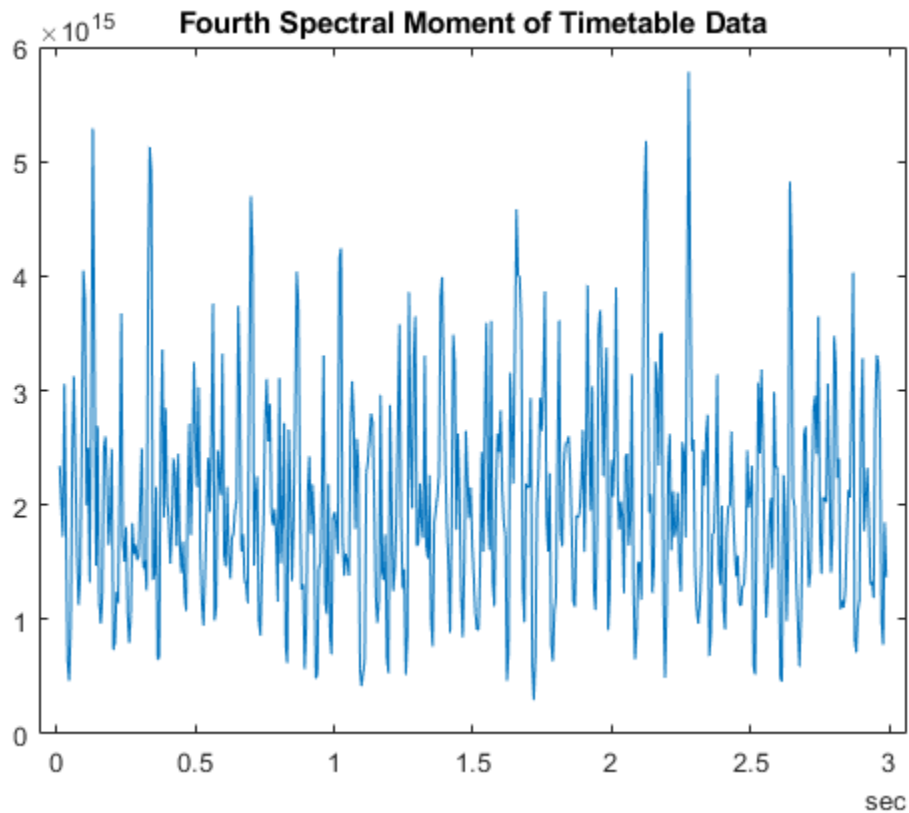
```
RowTimes: [524x1 duration]
StartTime: 0.011725 sec
SampleRate: 175.6403
TimeStep: 0.0056935 sec
CustomProperties: No custom properties are set.
Use addprop and rmprop to modify CustomProperties.
```

The returned `timetable` represents the moments in the variable 'CentralSpectralMoment2' and 'CentralSpectralMoment4', providing information not only on what specific moment was calculated, but whether it was centralized.

You can access the time and moment information directly from the `timetable` properties. Compute the second and fourth moments. Plot the fourth moment.

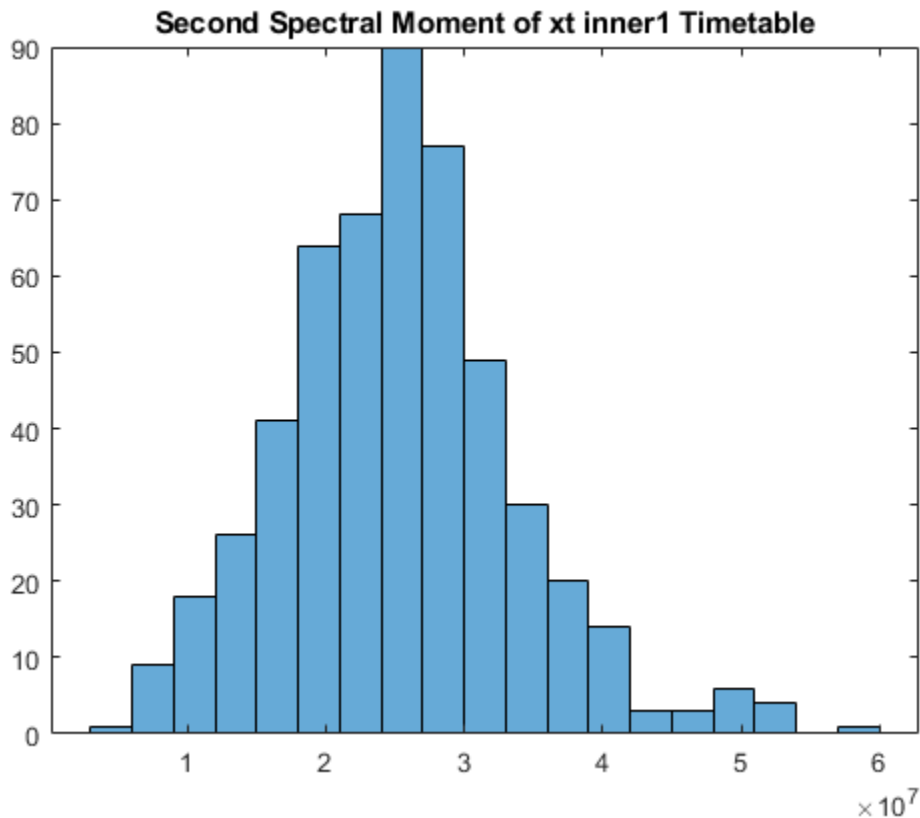
```
tt_inner1 = moments_xt_inner1.Time;
momentS_inner1_2 = moments_xt_inner1.CentralSpectralMoment2;
momentS_inner1_4 = moments_xt_inner1.CentralSpectralMoment4;

figure
plot(tt_inner1,momentS_inner1_4)
title('Fourth Spectral Moment of Timetable Data')
```



As is illustrated in “Plot the Conditional Spectral Moment of a Time Series Vector” on page 1-134, a histogram is a very useful visualization for moment data. Plot the histogram, directly referencing the `CentralSpectralMoment2` variable property.

```
figure
histogram(momentS_xt_inner1.CentralSpectralMoment2)
title('Second Spectral Moment of xt inner1 Timetable')
```



## Input Arguments

### **xt** — Signal Timetable

timetable

Signal Timetable for which `tfsmoment` returns the moments, specified as a `timetable` that contains a single variable with a single column. `xt` must contain increasing, finite row times. If the timetable has missing or duplicate time points, you can fix it using the tips in “Clean Timetable with Missing, Duplicate, or Nonuniform Times” (MATLAB). `xt` can be nonuniformly sampled, with the `pspectrum` constraint that the median time interval and the mean time interval must obey.

$$\frac{1}{100} < \frac{\text{Median time interval}}{\text{Mean time interval}} < 100.$$

For an example of timetable input, see “Find the Conditional Spectral Moments of Data Measurements in a Timetable” on page 1-147

## **order — Moment orders to return**

integer scalar | integer vector

Moment orders to return, specified as one of the following:

- Integer — Compute one moment
- Vector — Compute multiple moments at once.

Example: `momentS = tfsmoment(x,2)` specifies the second-order spectral moment (variance) of the time-frequency distribution of `x`.

Example: `momentS = tfsmoment(x,[1 2 3 4])` specifies the first four moment orders of the time-frequency distribution of `x`.

You can specify any order and number of orders, but low-order moments carry less computational burden and are better suited to real-time applications. The first four moment orders correspond to the statistical moments of a data set:

- 1 Mean
- 2 Variance
- 3 Skewness (degree of asymmetry about the mean)
- 4 Kurtosis (length of outlier tails in the distribution — a normal distribution has a kurtosis of 3)

For examples, see:

- Timetable data input — “Find the Conditional Spectral Moments of Data Measurements in a Timetable” on page 1-147
- Time-series vector data input — “Determine Multiple Orders of Conditional Spectral Moment for a Time Series” on page 1-140

## **x — Time-series signal**

vector

Time-series signal from which `tfsmoment` returns the moments, specified as a vector.

For an example of a time-series input, see “Plot the Conditional Spectral Moment of a Time Series Vector” on page 1-134

### **fs — Sample rate**

positive scalar

Sample rate of  $x$ , specified as positive scalar in hertz when  $x$  is uniformly sampled.

### **ts — Sample-time values**

duration scalar | vector | duration vector | datetime vector

Sample-time values, specified as one of the following:

- duration scalar — time interval between consecutive samples of  $X$ .
- Vector, duration array, or datetime array — time instant or duration corresponding to each element of  $x$ .

$ts$  can be nonuniform, with the `pspectrum` constraint that the median time interval and the mean time interval must obey:

$$\frac{1}{100} < \frac{\text{Median time interval}}{\text{Mean time interval}} < 100.$$

### **p — Power spectrogram or spectrum of signal**

vector | matrix

Power spectrogram or spectrum of a signal, specified as a matrix (spectrogram) or a column vector (spectrum).  $p$  contains an estimate of the short-term, time-localized power spectrum of a time-series signal. If you specify  $p$ , `tfsmoment` uses  $p$  rather than generate its own power spectrogram. For an example, see “Use a Customized Power Spectrogram to Compute the Conditional Spectral Moment” on page 1-143.

### **fp — Frequencies for p**

vector

Frequencies for power spectrogram or spectrum  $p$  when  $p$  is supplied explicitly to `tfsmoment`, specified as a vector in hertz. The length of  $fp$  must be equal to the number of rows in  $p$ .

### **tp — Time information for p**

vector | duration vector | datetime vector | duration scalar

Time information for power spectrogram or spectrum `p` when `p` is supplied explicitly to `tfsmoment`, specified as one of the following:

- Vector of time points, whose data type can be numeric, `duration`, or `datetime`. The length of vector `tp` must be equal to the number of columns in `p`.
- `duration` scalar that represents the time interval in `p`. The scalar form of `tp` can be used only when `p` is a power spectrogram matrix.
- For the special case where `p` is a column vector (power spectrum), `tp` can be a numeric, `duration`, or `datetime` scalar representing the time point of the spectrum.

## Name-Value Pair Arguments

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, . . . , NameN, ValueN`.

Example: `'Centralize', false, 'FrequencyLimits', [10 100]` computes the noncentralized conditional spectral moment for the portion of the signal ranging from 10 Hz to 100 Hz.

### **Centralize** — Centralize-moment option

`true` (default) | `false`

Centralize-moment option, specified as the comma-separated pair consisting of `'Centralize'` and a logical.

- If `Centralize` is `true`, then `tfsmoment` returns the centralized conditional moment by subtracting the conditional mean (which is the first moment) in the computation.
- If `Centralize` is `false`, then `tfsmoment` returns the noncentralized moment, preserving any data offset.

For an example, see “Calculate a Conditional Spectral Moment that is not Centralized” on page 1-145.

### **FrequencyLimits** — Frequency limits

full frequency band (default) | [`f1` `f2`]

Frequency limits to use, specified as the comma-separated pair consisting of `'FrequencyLimits'` and a two-element vector containing lower and upper bounds `f1`

and `f2` in hertz. This specification allows you to exclude a band of data at either end of the spectral range.

## Output Arguments

### **momentS** — Conditional spectral moment

timetable array | matrix

Conditional spectral moment returned as a `timetable` or a matrix.

- If you use `timetable` data `xt`, then `momentS` is a `timetable` array, containing variables which are the spectral moments for the orders specified in `order`. For an example, see “Find the Conditional Spectral Moments of Data Measurements in a Timetable” on page 1-147.
- If you use vector data `x`, or spectrogram data `p`, then `momentS` is an array whose columns represent the spectral moments. For an example, see “Determine Multiple Orders of Conditional Spectral Moment for a Time Series” on page 1-140.

### **t** — Times of moment estimates

double vector

Times of moment estimates in seconds. `t` results from the time windowing that the internal spectrogram computation computes. The spectrogram windows require less time resolution than the original sample vector. Therefore, the returned `t` vector is more compact than the input data vectors, as is `momentS`. If time information has been provided by sample rate or sample time, `t` starts from the center of the first time window. If time information has been provided in `duration` or `datetime` format, `t` preserves the start-time offset.

## Definitions

### Conditional Spectral Moments

The conditional spectral moments of a nonstationary signal comprise a set of time-varying parameters that characterize the signal spectrum as it evolves in time. They are related to the conditional temporal moments and the joint time-frequency moments. The conditional spectral moment is an integral function of frequency, given time, and marginal

distribution. The conditional temporal moment is an integral function of time, given frequency, and marginal distribution. The calculation of the joint time-frequency moment is a double integral that varies both time and frequency [1], [2].

Each moment is associated with a specific order, with the first four orders being the statistical properties of 1) mean, 2) variance, 3) skewness, and 4) kurtosis.

`tfsmoment` computes the conditional spectral moments of the time-frequency distribution for a signal `x`, for the orders specified in `order`. The function performs these steps:

- 1 Compute the spectrogram power spectrum,  $P(t,f)$ , of the input using the `pspectrum` function and uses it as a time-frequency distribution. If the syntax used supplies an existing  $P(t,f)$ , then `tfsmoment` uses that instead.

- 2 Estimate the conditional spectral moment  $\langle \omega^m \rangle_t$  of the signal using, for the noncentralized case:

$$\langle \omega^m \rangle_t = \frac{1}{P(t)} \int \omega^m P(t, \omega) d\omega,$$

where  $m$  is the order and  $P(t)$  is the marginal distribution.

For the centralized conditional spectral moment  $\mu_\omega^m(t)$ , the function uses

$$\mu_\omega^m(t) = \frac{1}{P(t)} \int \left( \omega - \langle \omega^1 \rangle_t \right)^m P(t, \omega) d\omega.$$

## References

- [1] Loughlin, P. J. "What Are the Time-Frequency Moments of a Signal?" *Advanced Signal Processing Algorithms, Architectures, and Implementations XI, SPIE Proceedings*. Vol. 4474, November 2001.
- [2] Loughlin, P., F. Cakrak, and L. Cohen. "Conditional Moment Analysis of Transients with Application to Helicopter Fault Data." *Mechanical Systems and Signal Processing*. Vol 14, Issue 4, 2000, pp. 511-522.



## See Also

`pspectrum` | `tfmoment` | `tftmoment`

**Introduced in R2018a**

## tftmoment

Conditional temporal moment of the time-frequency distribution of a signal

Time-frequency moments provide an efficient way to characterize signals whose frequencies change in time (that is, are nonstationary). Such signals can arise from machinery with degraded or failed hardware. Classical Fourier analysis cannot capture the time-varying frequency behavior. Time-frequency distribution generated by short-time Fourier transform (STFT) or other time-frequency analysis techniques can capture the time-varying behavior, but directly treating these distributions as features carries a high computational burden, and potentially introduces unrelated and undesirable feature characteristics. In contrast, distilling the time-frequency distribution results into low-dimension time-frequency moments provides a method for capturing the essential features of the signal in a much smaller data package. Using these moments significantly reduces the computational burden for feature extraction and comparison — a key benefit for real-time operation [1], [2].

The Predictive Maintenance Toolbox implements the three branches of time-frequency moment:

- Conditional spectral moment — `tfsmoment`
- Conditional temporal moment — `tftmoment`
- Joint time-frequency moment — `tfmoment`

## Syntax

```
momentT = tftmoment(xt,order)
momentT = tftmoment(x,fs,order)
momentT = tftmoment(x,ts,order)
momentT = tftmoment(p,fp,tp,order)
momentT = tftmoment( ____,Name,Value)
```

```
[momentT,f] = tftmoment( ____)
```

```
tftmoment( ____)
```

## Description

`momentT = tftmoment(xt,order)` returns the conditional temporal moment on page 1-173 of `timetable` `xt` as a matrix. The `momentT` variables provide the temporal moments for the orders you specify in `order`. The data in `xt` can be nonuniformly sampled.

`momentT = tftmoment(x,fs,order)` returns the conditional temporal moment of time-series vector `x`, sampled at rate `fs`. The moment is returned as a matrix, in which each column represents a temporal moment corresponding to each element in `order`. With this syntax, `x` must be uniformly sampled.

`momentT = tftmoment(x,ts,order)` returns the conditional temporal moment of `x` sampled at the time instants specified by `ts` in seconds.

- If `ts` is a scalar duration, then `tftmoment` applies it uniformly to all samples.
- If `ts` is a vector, then `tftmoment` applies each element to the corresponding sample in `x`. Use this syntax for nonuniform sampling.

`momentT = tftmoment(p,fp,tp,order)` returns the conditional temporal moment of a signal whose power spectrogram is `p`. `fp` contains the frequencies corresponding to the temporal estimate contained in `p`. `tp` contains the vector of time instants corresponding to the centers of the windowed segments used to compute short-time power spectrum estimates. Use this syntax when:

- You already have the power spectrogram you want to use.
- You want to customize the options for `pspectrum`, rather than accept the default `pspectrum` options that `tftmoment` applies. Use `pspectrum` first with the options you want, and then use the output `p` as input for `tftmoment`. This approach also allows you to plot the power spectrogram.

`momentT = tftmoment( ____,Name,Value)` specifies additional properties using name-value pair arguments. Options include moment centralization and time-limit specification.

You can use `Name,Value` with any of the input-argument combinations in previous syntaxes.

`[momentT,f] = tftmoment( ____ )` returns the frequency vector `f` associated with the moment matrix in `momentT`.

You can use `f` with any of the input-argument combinations in previous syntaxes.

`tftmoment( ___ )` with no output arguments plots the conditional temporal moment. The plot x-axis is frequency, and the plot y-axis is the corresponding temporal moment.

You can use this syntax with any of the input-argument combinations in previous syntaxes.

## Examples

### Plot the Conditional Temporal Moments of a Time Series Vector

Plot the conditional temporal moments of a time series using a plot-only approach and a return-data approach.

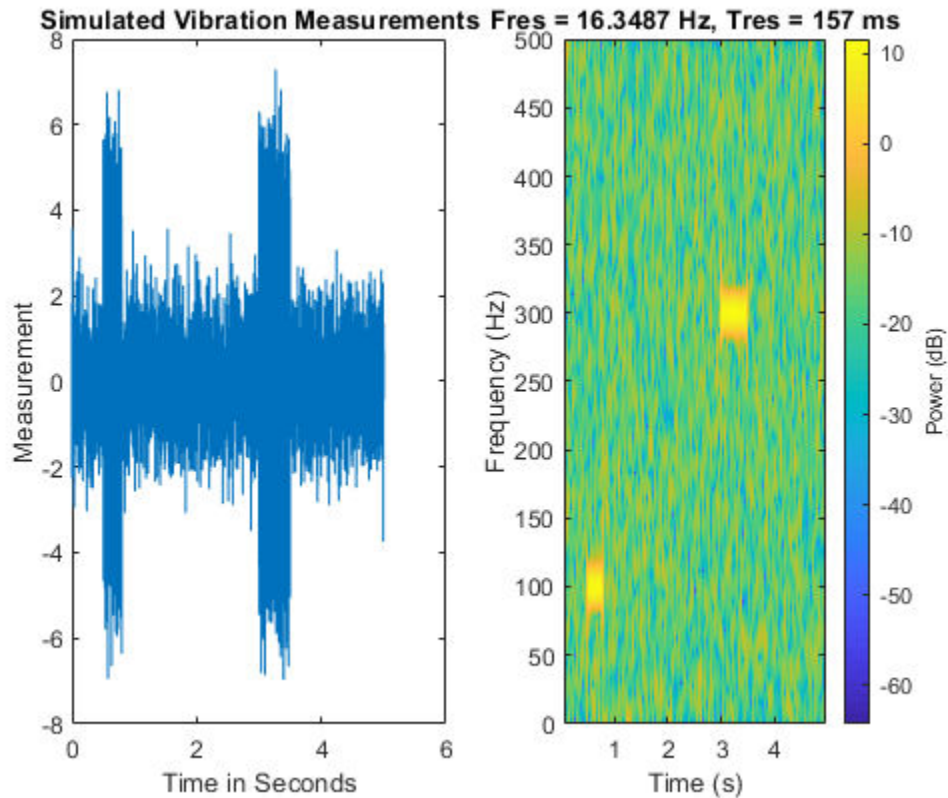
Load and plot the data, which consists of simulated vibration measurements for a system with a fault that causes periodic resonances. `x` is the vector of measurements, and `fs` is the sampling frequency.

```
load tftmoment_example x fs

ts=0:1/fs:(length(x)-1)/fs;
figure
subplot(1,2,1)
plot(ts,x)
xlabel('Time in Seconds')
ylabel('Measurement')
title('Simulated Vibration Measurements')
```

Use the function `pspectrum` with the `'spectrogram'` option to show the frequency content versus time.

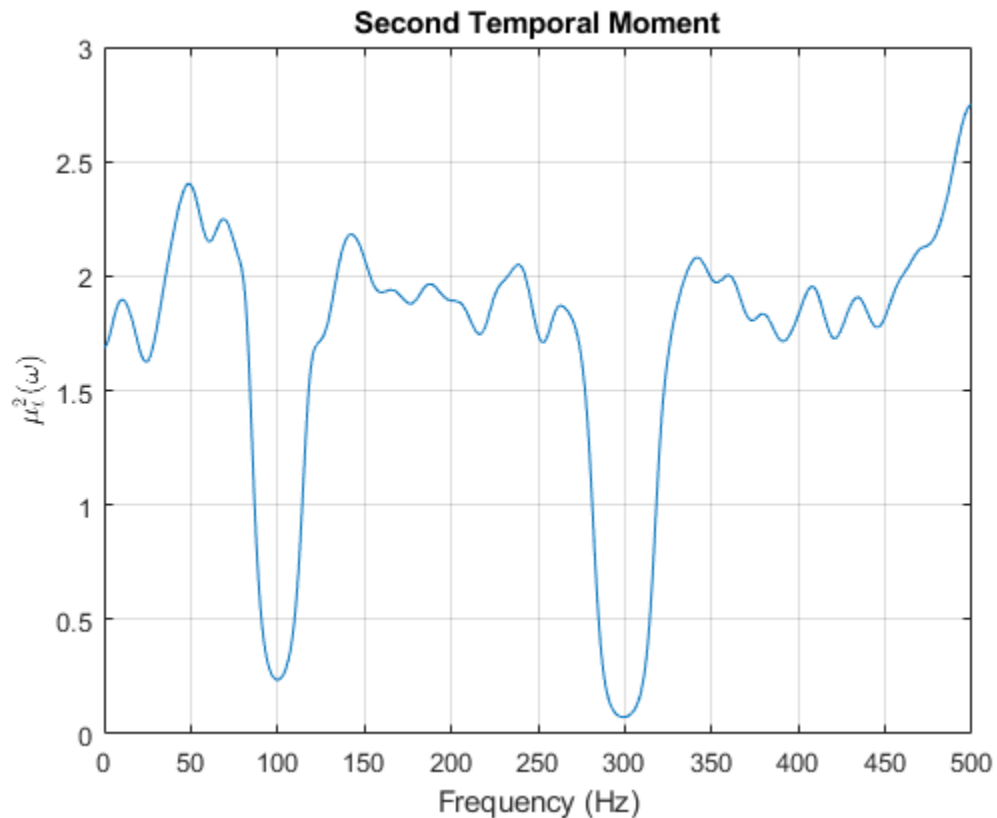
```
subplot(1,2,2)
pspectrum(x,ts,'spectrogram')
```



The spectrogram shows that the first burst is at 100 Hz, and the second burst is at 300 Hz. The 300-Hz burst is stronger than the 100-Hz burst by 70 dB.

Plot the second temporal moment (variance), using the plot-only approach with no output arguments and specifying `fs`.

```
figure
order = 2;
tftmoment(x,fs,order);title('Second Temporal Moment')
```



There are two distinct features in the plot at 100 and 300 Hz corresponding to the induced resonances shown by the spectrogram. The moments are much closer in magnitude than the spectral results were.

Now find the first four temporal moments, using the timeline `ts` that you already constructed. This time, use the form that returns both the moment vectors and the associated frequency vectors. Embed the order array as part of the input argument.

```
[momentT,f] = tftmoment(x,ts,[1 2 3 4]);
```

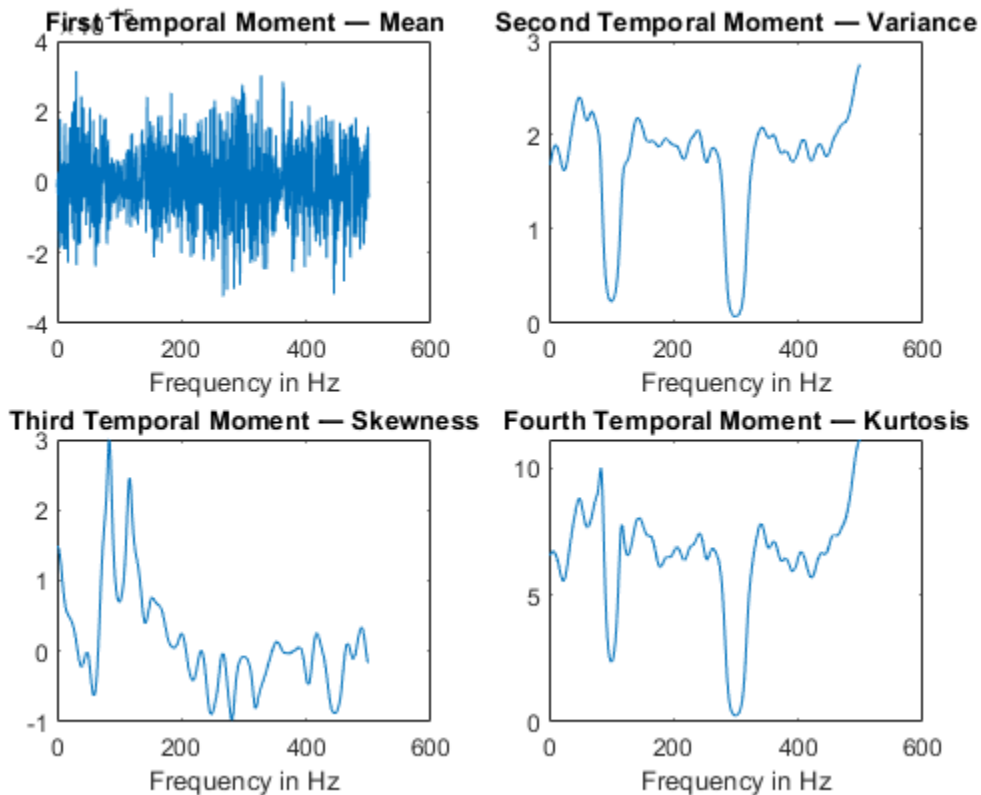
Each column of `momentT` contains the moment corresponding to one of the input orders.

```
momentT_1 = momentT(:,1);
momentT_2 = momentT(:,2);
```

```
momentT_3 = momentT(:,3);  
momentT_4 = momentT(:,4);
```

Plot the four moments separately to compare the shapes.

```
figure  
subplot(2,2,1)  
plot(f,momentT_1)  
title('First Temporal Moment – Mean')  
xlabel('Frequency in Hz')  
  
subplot(2,2,2)  
plot(f,momentT_2)  
title('Second Temporal Moment – Variance')  
xlabel('Frequency in Hz')  
  
subplot(2,2,3)  
plot(f,momentT_3)  
title('Third Temporal Moment – Skewness')  
xlabel('Frequency in Hz')  
  
subplot(2,2,4)  
plot(f,momentT_4)  
title('Fourth Temporal Moment – Kurtosis')  
xlabel('Frequency in Hz')
```



For the data in this example, the second and fourth temporal moments show the clearest features for the faulty resonance.

### **Use an Existing Power Spectrogram to Compute the Conditional Temporal Moment**

By default, `tftsmoment` calls the function `pspectrum` internally to generate the power spectrogram that `tftmoment` uses for the moment computation. You can also import an existing power spectrogram for `tftmoment` to use instead. This capability is useful if you already have a power spectrogram as a starting point, or if you want to customize the `pspectrum` options by generating the spectrogram explicitly first.



Input a power spectrogram that has already been generated using default options. Compare the resulting temporal-moment plot with one that `tftmoment` generates using its own `spectrum` default options. The results should be the same.

Load the data, which consists of simulated vibration measurements for a system with a fault that causes periodic resonances. `p` is the previously computed spectrogram, `fp` and `tp` are the frequency and time vectors associated with `p`, `x` is the original vector of measurements, and `fs` is the sampling frequency.

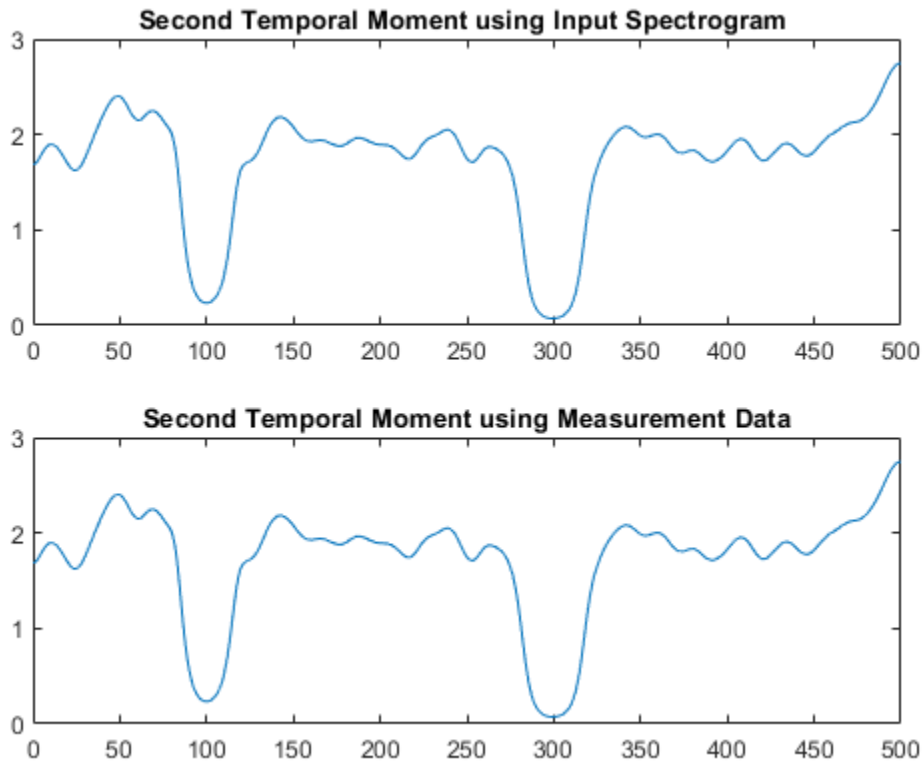
```
load tftmoment_example p fp tp x fs
```

Determine the second temporal moment using the spectrogram and its associated frequency and time vectors. Plot the moment.

```
[momentT_p,f_p] = tftmoment(p,fp,tp,2);  
figure  
subplot(2,1,1)  
plot(f_p,momentT_p)  
title('Second Temporal Moment using Input Spectrogram ')
```

Now find and plot the second temporal moments using the original data and sampling rate.

```
[momentT,f] = tftmoment(x,fs,2);  
subplot(2,1,2)  
plot(f,momentT)  
title('Second Temporal Moment using Measurement Data')
```



As expected, the plots match since the default `pspectrum` options were used for both. This result demonstrates the equivalence between the two approaches when there is no customization.

### Find the Conditional Temporal Moments of Data Measurements in a Timetable

Real-world measurements often come packaged as part of a time-stamped table that records actual time and readings rather than relative times. You can use the `timetable` format for capturing this data. This example shows how `tftmoment` operates with a timetable input, in contrast to the data vector inputs used for the other `tftmoment`

examples, such as “Plot the Conditional Temporal Moments of a Time Series Vector” on page 1-160.

Load the data, which consists of a single timetable (`xt_inner1`) containing measurement readings and time information for a piece of machinery. Examine the properties of the timetable.

```
load tftmoment_tdata.mat xt_inner1;
xt_inner1.Properties

ans =
    TimetableProperties with properties:

        Description: ''
        UserData: []
        DimensionNames: {'Time' 'Variables'}
        VariableNames: {'x_inner1'}
        VariableDescriptions: {}
        VariableUnits: {}
        VariableContinuity: []
        RowTimes: [146484x1 duration]
        StartTime: 0 sec
        SampleRate: 4.8828e+04
        TimeStep: 2.048e-05 sec
        CustomProperties: No custom properties are set.
        Use addprop and rmprop to modify CustomProperties.
```

This table consists of dimensions `Time` and the `Variables`, where the only variable is `x_inner1`.

Find the second and fourth conditional temporal moments (`order = [2 4]`) for the data in the timetable.

```
order = [2 4];
[momentT_xt_inner1,f] = tftmoment(xt_inner1,order);
size(momentT_xt_inner1)

ans = 1x2

    1024         2
```

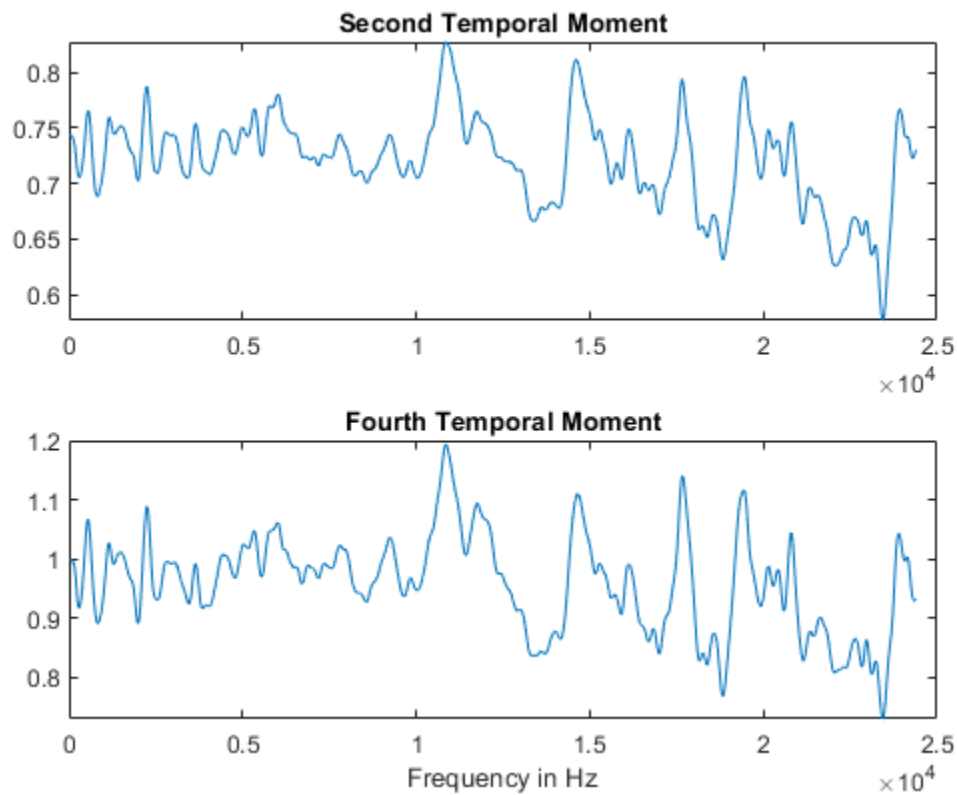
The temporal moments are represented by the columns of `momentT_xt_inner1`, just as they would be for a moment taken from a time series vector input.

Plot the moments versus returned frequency vector  $f$ .

```
momentT_inner1_2 = momentT_xt_inner1(:,1);  
momentT_inner1_4 = momentT_xt_inner1(:,2);
```

```
figure  
subplot(2,1,1)  
plot(f,momentT_inner1_2)  
title("Second Temporal Moment")
```

```
subplot(2,1,2)  
plot(f,momentT_inner1_4)  
title("Fourth Temporal Moment")  
xlabel('Frequency in Hz')
```



## Input Arguments

### **xt** — Time-series signal

timetable

Time-series signal for which `tftmoment` returns the moments, specified as a `timetable` that contains a single variable with a single column. `xt` must contain increasing, finite row times. If the timetable has missing or duplicate time points, you can fix it using the tips in “Clean Timetable with Missing, Duplicate, or Nonuniform Times” (MATLAB). `xt` can be nonuniformly sampled, with the `pspectrum` constraint that the median time interval and the mean time interval must obey:

$$\frac{1}{100} < \frac{\text{Median time interval}}{\text{Mean time interval}} < 100.$$

For an example of `timetable` input, see “Find the Conditional Temporal Moments of Data Measurements in a Timetable” on page 1-166

### **order** — Moment orders to return

integer scalar | integer vector

Moment orders to return, specified as one of the following:

- Integer — Compute one moment.
- Vector — Compute multiple moments at once.

Example: `momentT = tftmoment(x,2)` specifies the second-order temporal moment (variance) of the time-frequency distribution of `x`.

Example: `momentT = tftmoment(x,[1 2 3 4])` specifies the first four moment orders of the time-frequency distribution of `x`.

You can specify any order and number of orders, but low-order moments carry less computational burden and are better suited to real-time applications. The first four moment orders correspond to the statistical moments of a data set:

- 1 Mean ("group delay" for temporal data)
- 2 Variance

- 3 Skewness (degree of asymmetry about the mean)
- 4 Kurtosis (length of outlier tails in the distribution — a normal distribution has a kurtosis of 3)

For examples, see:

- Timetable data input — “Find the Conditional Temporal Moments of Data Measurements in a Timetable” on page 1-166
- Time-series vector data input — “Plot the Conditional Temporal Moments of a Time Series Vector” on page 1-160

## **x — Time-series signal**

vector

Time-series signal from which `tftmoment` returns the moments, specified as a vector.

For an example of a time-series input, see “Plot the Conditional Temporal Moments of a Time Series Vector” on page 1-160

## **fs — Sample rate**

positive scalar

Sample rate of `x`, specified as positive scalar in hertz when `x` is uniformly sampled.

## **ts — Sample-time values**

duration scalar | vector | duration vector | datetime vector

Sample-time values, specified as one of the following:

- duration scalar — time interval between consecutive samples of `X`.
- Vector, duration array, or datetime array — time instant or duration corresponding to each element of `x`.

`ts` can be nonuniform, with the `pspectrum` constraint that the median time interval and the mean time interval must obey:

$$\frac{1}{100} < \frac{\text{Median time interval}}{\text{Mean time interval}} < 100.$$

## **p — Power spectrogram or spectrum of signal**

matrix | vector

Power spectrogram or spectrum of a signal, specified as a matrix (spectrogram) or a column vector (spectrum). `p` contains an estimate of the short-term, time-localized power spectrum of a time-series signal. If you specify `p`, then `tftmoment` uses `p` rather than generate its own power spectrogram. For an example, see “Use a Customized Power Spectrogram to Compute the Conditional Spectral Moment” on page 1-143.

### **fp — Frequencies for p**

vector

Frequencies for power spectrogram or spectrum `p` when `p` is supplied explicitly to `tftmoment`, specified as a vector in hertz. The length of `fp` must be equal to the number of rows in `p`.

### **tp — Time information for p**

vector | duration vector | datetime vector | duration scalar

Time information for power spectrogram or spectrum `p` when `p` is supplied explicitly to `tftmoment`, specified as one of the following:

- Vector of time points, whose data type can be numeric, `duration`, or `datetime`. The length of vector `tp` must be equal to the number of columns in `p`.
- `duration` scalar that represents the time interval in `p`. The scalar form of `tp` can be used only when `p` is a power spectrogram matrix.
- For the special case where `p` is a column vector (power spectrum), `tp` can be a numeric, `duration`, or `datetime` scalar representing the time point of the spectrum.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1,Value1,...,NameN,ValueN`.

Example: `'Centralize',false,'TimeLimits',[20 100]` computes the noncentralized conditional temporal moment for the portion of the signal ranging from 20 sec to 100 sec.

### **Centralize — Centralize-moment option**

true (default) | false

Centralize-moment option, specified as the comma-separated pair consisting of 'Centralize' and a logical.

- If `Centralize` is `true`, then `tftmoment` returns the centralized conditional moment by subtracting the conditional mean (which is the first moment) in the computation.
- If `Centralize` is `false`, then `tftmoment` returns the noncentralized moment, preserving any data offset.

Example: `momentT = tftmoment(x,2,'Centralize',false)`.

## **TimeLimits — Time Limits**

full timespan (default) | [t1 t2]

Time limits, specified as the comma-separated pair consisting of 'TimeLimits' and a two-element vector containing lower and upper bounds `t1` and `t2` in the same units as `ts`, and of the data types:

- Numeric or duration when `fs` or a scalar `ts` are specified, or when `ts` is a numeric or duration vector
- Numeric, duration, or `datetime` when `ts` is specified as a `datetime` vector

This specification allows you to extract a temporal section of data from a longer data set.

## **Output Arguments**

### **momentT — Conditional temporal moment**

matrix

Conditional temporal moment returned as a matrix whose columns represent the temporal moments.

`momentT` is a matrix with one or more columns, regardless of whether the input data is timetable `xt`, time-series vector `x`, or spectrogram data `p`.

### **f — Frequencies of moment estimates**

double vector

Frequencies of moment estimates in hertz, specified as a double vector. For an example, see “Plot the Conditional Temporal Moments of a Time Series Vector” on page 1-160



## Definitions

### Conditional Temporal Moments

The conditional temporal moments of a nonstationary signal comprise a set of time-varying parameters that characterize the group delay as it evolves in time. They are related to the conditional spectral moment on page 1-155 and the joint time-frequency moments. The conditional spectral moment is an integral function of frequency, given time, and marginal distribution. The conditional temporal moment is an integral function of time, given frequency, and marginal distribution. The joint time-frequency moment is a double integral that varies both time and frequency [1], [2].

Each moment is associated with a specific order, with the first four orders being the statistical properties of 1) mean, 2) variance, 3) skewness, and 4) kurtosis.

`tftmoment` computes the conditional temporal moments of the time-frequency distribution for a signal  $x$ , for the orders specified in `order`. The function performs these steps:

- 1 Compute the spectrogram power spectrum,  $P(t, f)$ , of the input using the `pspectrum` function and uses it as a time-frequency distribution. If the syntax used supplies an existing  $P(t, f)$ , then `tftmoment` uses that instead.

- 2 Estimate the conditional temporal moment  $\langle t^n \rangle_\omega$  of the signal using, for the non-centralized case:

$$\langle t^n \rangle_\omega = \frac{1}{P(\omega)} \int t^n P(t, \omega) dt,$$

where  $m$  is the order and  $P(t)$  is the marginal distribution.

For the centralized conditional temporal moment  $\mu_t^n(\omega)$ , the function uses

$$\mu_t^n(\omega) = \frac{1}{P(\omega)} \int \left( t - \langle t^1 \rangle_\omega \right)^n P(t, \omega) dt.$$

## References

- [1] Loughlin, P. J. "What are the time-frequency moments of a signal?" *Advanced Signal Processing Algorithms, Architectures, and Implementations XI, SPIE Proceedings*. Vol. 4474, November 2001.
- [2] Loughlin, P., F. Cakrak, and L. Cohen. "Conditional moment analysis of transients with application to helicopter fault data." *Mechanical Systems and Signal Processing*. Vol 14, Issue 4, 2000, pp. 511-522.

## See Also

`pspectrum` | `tfmoment` | `tfsmoment`

**Introduced in R2018a**

# trendability

Measure of similarity between trajectories of condition indicators

## Syntax

```
Y = trendability(X)
Y = trendability(X, lifetimeVar)
Y = trendability(X, lifetimeVar, dataVar)
Y = trendability(X, lifetimeVar, dataVar, memberVar)
Y = trendability( ____, Name, Value)
```

```
trendability( ____, )
```

## Description

`Y = trendability(X)` returns the trendability of the lifetime data `X`. Use `trendability` as measure of similarity between the trajectories of a feature measured in several run-to-failure experiments. A more trendable feature has trajectories with the same underlying shape. The values of `Y` range from 0 to 1, where `Y` is 1 if `X` is perfectly trendable and 0 if `X` is non-trendable.

`Y = trendability(X, lifetimeVar)` returns the trendability of the lifetime data `X` using the lifetime variable `lifetimeVar`.

`Y = trendability(X, lifetimeVar, dataVar)` returns the trendability of the lifetime data `X` using the data variables specified by `dataVar`.

`Y = trendability(X, lifetimeVar, dataVar, memberVar)` returns the trendability of the lifetime data `X` using the lifetime variable `lifetimeVar`, the data variables specified by `dataVar`, and the member variable `memberVar`.

`Y = trendability( ____, Name, Value)` estimates the trendability with additional options specified by one or more `Name, Value` pair arguments. You can use this syntax with any of the previous input-argument combinations.

`trendability( ___ )` with no output arguments plots a bar chart of ranked trendability values.

## Examples

### Trendability of Data in Cell Array of Matrices

In this example, consider the lifetime data of 10 identical machines with the following 6 potential prognostic parameters — constant, linear, quadratic, cubic, logarithmic, and periodic. The data set `machineDataCellArray.mat` contains `C` which is a `1x10` cell array of matrices where each element of the cell array is a matrix that contains the lifetime data of a machine. For each matrix in the cell array, the first column contains the time while the other columns contain the data variables.

Load the lifetime data and visualize it against time.

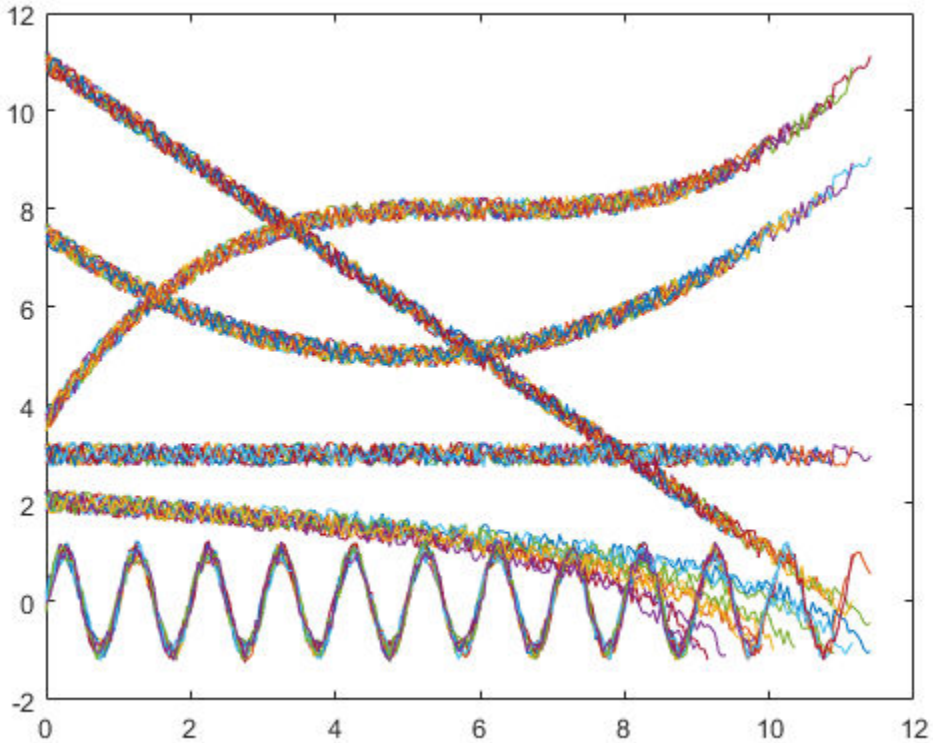
```
load('machineDataCellArray.mat','C')
display(C)
```

```
C = 1x10 cell array
  Columns 1 through 4
    {219x7 double}    {189x7 double}    {202x7 double}    {199x7 double}

  Columns 5 through 8
    {229x7 double}    {184x7 double}    {224x7 double}    {208x7 double}

  Columns 9 through 10
    {181x7 double}    {197x7 double}
```

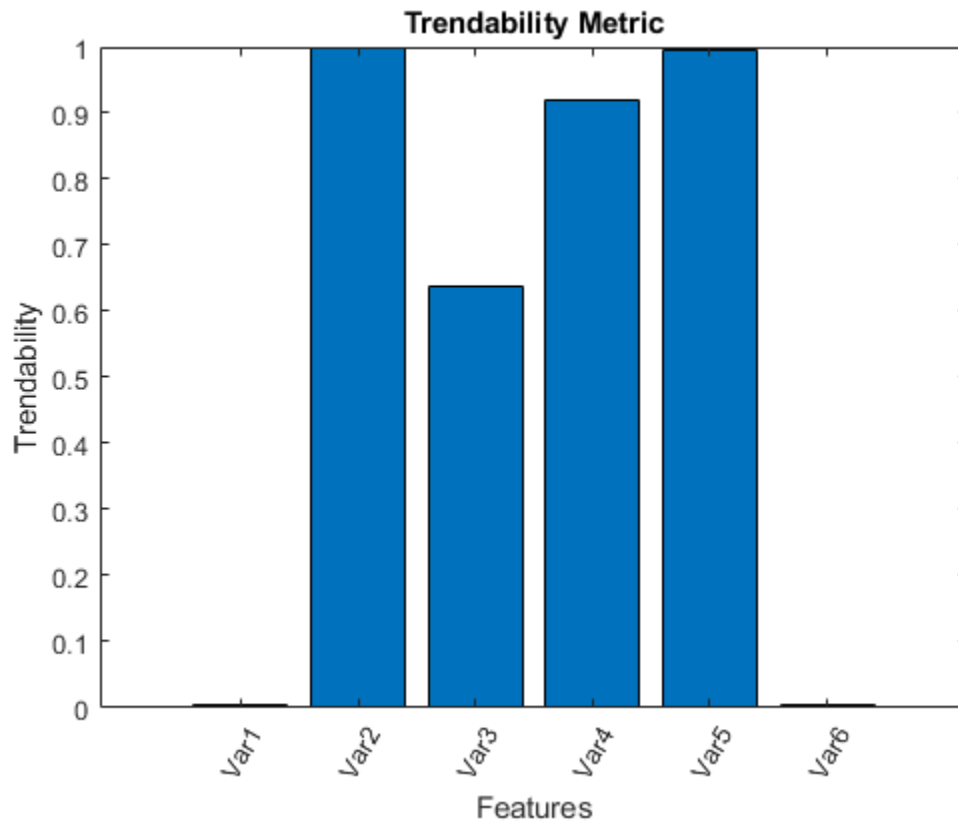
```
for k = 1:length(C)
    plot(C{k}(:,1), C{k}(:,2:end));
    hold on;
end
```



Observe the 6 different condition indicators—constant, linear, quadratic, cubic, logarithmic, and periodic—for all 10 machines on the plot.

Visualize the trendability of the potential prognostic features.

```
trendability(C)
```



From the histogram plot, observe that the features Var2 and Var5 have trendability values of 1. Hence, these features are more appropriate for remaining useful life predictions since they are the best indicators of machine health.

### **Trendability of Data in Cell Array of Tables**

In this example, consider the lifetime data of 10 identical machines with the following 6 potential prognostic parameters — constant, linear, quadratic, cubic, logarithmic, and periodic. The data set `machineDataTable.mat` contains `T`, which is a `1x10` cell array of

tables where each element of the cell array contains a table of lifetime data for a machine.

Load and display the data.

```
load('machineDataTable.mat','T');
display(T)
```

```
T = 1x10 cell array
Columns 1 through 4
    {219x7 table}    {189x7 table}    {202x7 table}    {199x7 table}
Columns 5 through 8
    {229x7 table}    {184x7 table}    {224x7 table}    {208x7 table}
Columns 9 through 10
    {181x7 table}    {197x7 table}
```

```
head(T{1},2)
```

```
ans=2x7 table
    Time    Constant    Linear    Quadratic    Cubic    Logarithmic    Periodic
    -----
    0        3.2029    11.203   7.7029    3.8829    2.2517    0.2029
    0.05     2.8135    10.763   7.2637    3.6006    1.8579    0.12251
```

Note that every table in the cell array contains the lifetime variable 'Time' and the data variables 'Constant', 'Linear', 'Quadratic', 'Cubic', 'Logarithmic', and 'Periodic'.

Compute trendability with Time as the lifetime variable.

```
Y = trendability(T,'Time')
```

```
Y=1x6 table
    Constant    Linear    Quadratic    Cubic    Logarithmic    Periodic
    -----
    0.0035529    0.99984    0.63753    0.92057    0.99582    0.0041995
```

From the resultant table of trendability values, observe that the linear, cubic, and logarithmic features have values closer to 1. Hence, these three features are more appropriate for predicting remaining useful life since they are the best indicators of machine health.

## Visualize Trendability of Lifetime Data in Ensemble Datastore

Consider the lifetime data of 4 machines. Each machine has 4 fault codes for the potential condition indicators—voltage, current, and power. `trendabilityEnsemble.zip` is a collection of 4 files where every file contains a timetable of lifetime data for each machine - `tbl1.mat`, `tbl2.mat`, `tbl3.mat` and `tbl4.mat`. You can also use files containing data for multiple machines. For each timetable, the organization of the data is as follows:

Time	Voltage	Current	Power	FaultCode	Machine

Extract the compressed files, read the data in the timetables, and create a `fileEnsembleDatastore` object using the timetable data. For more information on creating a file ensemble datastore, see `fileEnsembleDatastore`.

```
unzip trendabilityEnsemble.zip;
ens = fileEnsembleDatastore(pwd, '.mat');
ens.DataVariables = {'Voltage', 'Current', 'Power', 'FaultCode', 'Machine'};
% Make sure that the function for reading data is on path
addpath(fullfile(matlabroot, 'examples', 'predmaint', 'main'))
ens.ReadFcn = @readtable_data;
ens.SelectedVariables = {'Voltage', 'Current', 'Power', 'FaultCode', 'Machine'};
```

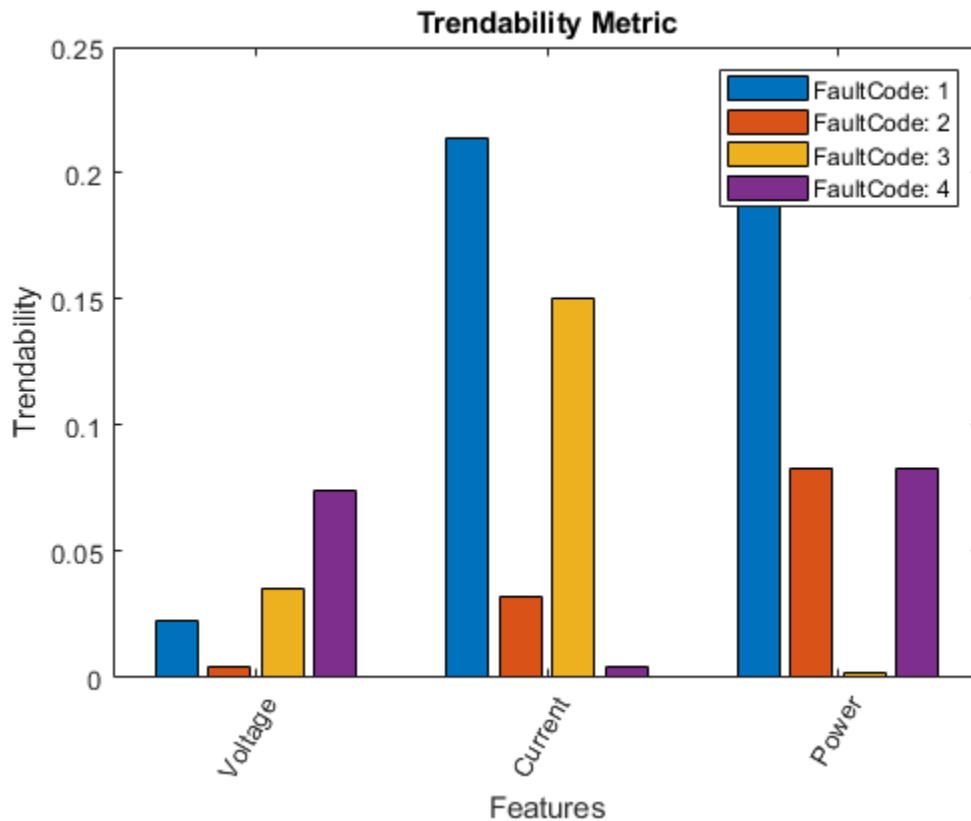
Visualize the trendability of the potential prognostic features with 'Machine' as the member variable and group the lifetime data by 'FaultCode'. Grouping the lifetime data ensures that `trendability` calculates the metric for each fault code separately.

```
trendability(ens, 'MemberVariable', 'Machine', 'GroupBy', 'FaultCode');
```

```
Starting parallel pool (parpool) using the 'local' profile ...
connected to 12 workers.
Evaluating tall expression using the Parallel Pool 'local':
- Pass 1 of 1: Completed in 4.6 sec
Evaluation completed in 8.9 sec
```



```
Evaluating tall expression using the Parallel Pool 'local':  
- Pass 1 of 1: Completed in 2.1 sec  
Evaluation completed in 2.8 sec  
Evaluating tall expression using the Parallel Pool 'local':  
- Pass 1 of 1: Completed in 4 sec  
Evaluation completed in 4 sec
```



`trendability` returns a histogram plot with the features ranked by their trendability values. A higher trendability value indicates a more suitable prognostic parameter. For instance, the candidate feature `Current` has the highest degree of trendability for machines with `FaultCode 1`.

```
rmpath(fullfile(matlabroot, 'examples', 'predmaint', 'main')) % Reset path
```

## Input Arguments

### **X — Lifetime data**

cell array of matrices | cell array of tables and timetables | `fileEnsembleDatastore` object | table | timetable

Lifetime data, specified as a cell array of matrices, cell array of tables and timetables, `fileEnsembleDatastore` object, table, or timetable. Lifetime data contains run-to-failure data of the systems being monitored. The term *lifetime* here refers to the life of the machine defined in terms of the units you use to measure system life. Units of lifetime can be quantities such as the distance traveled (miles), fuel consumed (gallons), or time since the start of operation (days).

If X is

- a cell array of matrices or tables, the function assumes that each matrix or table contains columns of lifetime data for a system. Each column of every matrix or table, except the first column, contains data for a prognostic variable. `'Var1'`, `'Var2'`, ... can be used to refer to the matrix columns that contain the lifetime data. For instance, the file `machineDataCellArray.mat` contains a 1-by-10 cell array of matrices C, where each of the 10 matrices contains data for a particular machine.
- a table or timetable, the function assumes that each column, except the first one, contains columns of lifetime data. The table variable names can be used to refer to the columns that contain the lifetime data. If `lifetimeVar` is not specified when X is a table, then the first data column is used as the lifetime variable.
- a `fileEnsembleDatastore` object, specify the data variables `dataVar` and member variables `memberVar` to be used. If `lifetimeVar` is not specified, then the first data column is used as the lifetime variable for computation.

Each numerical member in X is of type `double`.

### **lifetimeVar — Lifetime variable**

string | character vector

Lifetime variable, specified as a string or character vector. `lifetimeVar` measures the lifetime of the systems being monitored and the lifetime data is sorted with respect to `lifetimeVar`. The value of `lifetimeVar` must be a valid ensemble or table variable name.

For a cell array of matrices, the value 'Time' can be used to refer to the first column of each matrix, which is assumed to contain the lifetime variable. For instance, the file `machineDataCellArray.mat` contains the cell array `C`, where the first column in each matrix contains the lifetime variable while the other columns contain the data variables.

### **dataVar — Data variables**

string array | character vector | cell array of character vectors

Data variables, specified as a string array, character vector, or cell array of character vectors. Data variables are the main content of the members of an ensemble. Data variables can include measured data or derived data for the analysis and development of predictive maintenance algorithms.

If `X` is

- a `fileEnsembleDatastore` object, the value of `dataVar` supersedes the `DataVariables` property of the ensemble.
- a cell array of matrices, the value 'Time' can be used to refer to the first column of each matrix, that is, the lifetime variable `lifetimeVar`. 'Var1', 'Var2', ... can be used to refer to the other matrix columns which contain the lifetime data. For instance, the file `machineDataCellArray.mat` contains the cell array `C` where the first column in each matrix contains the lifetime variable. The other columns in the cell array `C` contain the data variables.
- a table, the table variable names can be used to refer to the columns which contain the lifetime data.

The values of `dataVar` must be valid ensemble or table variable names. If `dataVar` is not specified, the computation includes all data columns except the one specified in `lifetimeVar`. For instance, suppose that each entry in a cell array is a table with variables `A`, `B`, `C`, and `D`. Setting `dataVar` to `["A", "D"]` uses only `A` and `D` for the computation while `C` and `D` are ignored.

### **memberVar — Member variable**

string | character vector

Member variable, specified as a string or character vector. Use `memberVar` to specify the variable for identifying the systems or machines in lifetime data `X`. For instance, in the `fileEnsembleDatastore` object, the fifth column in each timetable contains numbers that identify data from a particular machine. The column name corresponds to the member variable `memberVar`.

memberVar is ignored when X is specified as a cell array of matrices or tables.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of Name, Value arguments. Name is the argument name and Value is the corresponding value. Name must appear inside quotes. You can specify several name and value pair arguments in any order as Name1, Value1, ..., NameN, ValueN.

Example: ..., 'Method', 'rank'

### **LifeTimeVariable — Lifetime variable**

strings(0) (default) | string | character vector

Lifetime variable, specified as the comma-separated pair consisting of 'LifeTimeVariable' and either a string or character vector. If 'LifeTimeVariable' is not specified, then the first data column is used.

'LifeTimeVariable' is equivalent to the input argument lifetimeVar.

### **DataVariables — Data variables**

strings(0) (default) | string array | character vector | cell array of character vectors

Data variables, specified as the comma-separated pair consisting of 'DataVariables' and either a string array, character vector or cell array of character vectors.

'DataVariables' is equivalent to the input argument dataVar.

### **MemberVariable — Member variables**

[] (default) | string | character vector

Member variables, specified as the comma-separated pair consisting of 'MemberVariable' and either a string or character vector.

'MemberVariable' is equivalent to the input argument memberVar.

### **GroupBy — Grouping criterion**

[] (default) | string | character vector

Grouping criterion, specified as the comma-separated pair consisting of 'GroupBy' and either a string or character vector. Use 'GroupBy' to specify the variables for grouping the lifetime data X by operating conditions.

The function computes the metric separately for each group that results from applying the criterion, such as a fault condition, specified by 'GroupBy'. For instance, in the `fileEnsembleDatastore` object `ens`, the fourth column in each timetable in `ens` contains the variable 'FaultCode'. The metric is computed for each machine by grouping the data by 'FaultCode'.

You can only group variables when `X` is defined as a `fileEnsembleDatastore` object, table, timetable, or cell array of tables or timetables.

### **WindowSize — Size of the centered moving average window for data smoothing**

[] (default) | scalar | two-element vector

Size of the centered moving average window for data smoothing, specified as the comma-separated pair consisting of 'WindowSize' and either a scalar or two-element vector. A Savitzky-Golay filter is used for data smoothing. For more information, see `smoothdata`.

If 'WindowSize' is not specified, the window length is automatically determined from lifetime data `X` using `smoothdata(X, 'sgolay')`. Set 'WindowSize' to 0 to turn off data smoothing.

## **Output Arguments**

### **Y — Trendability of lifetime data**

vector | table

Trendability of lifetime data, returned as a vector or table.

Trendability is the measure of similarity between the trajectories of a feature measured in several run-to-failure experiments. A more trendable feature has trajectories with the same underlying shape. As a system gets progressively closer to failure, a suitable condition indicator is typically highly trendable. Conversely, any feature that is non-trendable is a less suitable condition indicator. The values of `Y` range from 0 to 1.

- `Y` is 1 if `X` is perfectly trendable.
- `Y` is 0 if `X` is perfectly non-trendable.

Selecting appropriate estimation parameters out of all available features is the first step in building a reliable remaining useful life prediction engine. The trendability values in `Y` are useful to determine which condition indicators best track the degradation process of

systems being monitored. The higher the trendability, the more desirable the feature is for prognostics.

When 'GroupBy' is not specified, then Y is returned as a row vector or single-row table. Conversely, when 'GroupBy' is specified, then each row in Y corresponds to one group.

## Limitations

- When X is a tall table or tall timetable, `trendability` nevertheless loads the complete array into memory using `gather`. If the memory available is inadequate, then `trendability` returns an error.

## Algorithms

The computation of trendability uses this formula:

$$\text{trendability} = \min_{j,k} \left| \text{corr}(x_j, x_k) \right|, \quad j, k = 1, \dots, M$$

where  $x_j$  represents the vector of measurements of a feature on the  $j^{\text{th}}$  system and the variable  $M$  is the number of systems monitored.

When  $x_j$  and  $x_k$  have different lengths, the shorter vector is resampled to match the length of the longer vector. To facilitate this process, their time vectors are first normalized to percent lifetime, that is, [0%, 100%].

## References

- [1] Coble, J., and J. W. Hines. "Identifying Optimal Prognostic Parameters from Data: A Genetic Algorithms Approach." In *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. 2009.
- [2] Coble, J. "Merging Data Sources to Predict Remaining Useful Life - An Automated Method to Identify Prognostics Parameters." Ph.D. Thesis. University of Tennessee, Knoxville, TN, 2010.
- [3] Lei, Y. *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Xi'an, China: Xi'an Jiaotong University Press, 2017.

- [4] Lofti, S., J. B. Ali, E. Bechhoefer, and M. Benbouzid. "Wind turbine high-speed shaft bearings health prognosis through a spectral Kurtosis-derived indices and SVR." *Applied Acoustics* Vol. 120, 2017, pp. 1-8.

## **See Also**

`fileEnsembleDatastore` | `monotonicity` | `prognosability`

**Introduced in R2018b**

## tsadifference

Difference signal of a time-synchronous averaged signal

### Syntax

```
Y = tsadifference(X,fs,rpm,orderList)
Y = tsadifference(X,t,rpm,orderList)
Y = tsadifference(XT,rpm,orderList)
[Y,S] = tsadifference(____)
____ = tsadifference(____)

tsadifference(____)
```

### Description

`Y = tsadifference(X,fs,rpm,orderList)` computes the difference signal `Y` of the time-synchronous averaged (TSA) signal vector `X` using sampling rate `fs`, the rotational speed `rpm`, and the orders to be filtered `orderList`. `Y` is computed by removing the residual signal, the value of 'NumSidebands', and their respective harmonics from `X`. For more information on residual signal, see `tsaresidual`.

You can use `Y` to further extract condition indicators of rotating machinery for predictive maintenance. For example, extracting the FM4 indicator from `Y` is useful to detect faults isolated to only a limited number of teeth in a gear mesh.

`Y = tsadifference(X,t,rpm,orderList)` computes the difference signal `Y` of the TSA signal vector `X` with corresponding time values from `t`.

`Y = tsadifference(XT,rpm,orderList)` computes the difference signal `Y` of the TSA signal stored in the timetable `XT`. `XT` must contain a single numeric column variable.

`[Y,S] = tsadifference(____)` returns the amplitude spectrum `S` of the difference signal `Y`. `S` is the amplitude spectrum computed using the normalized fast Fourier transform (FFT) of `Y`.



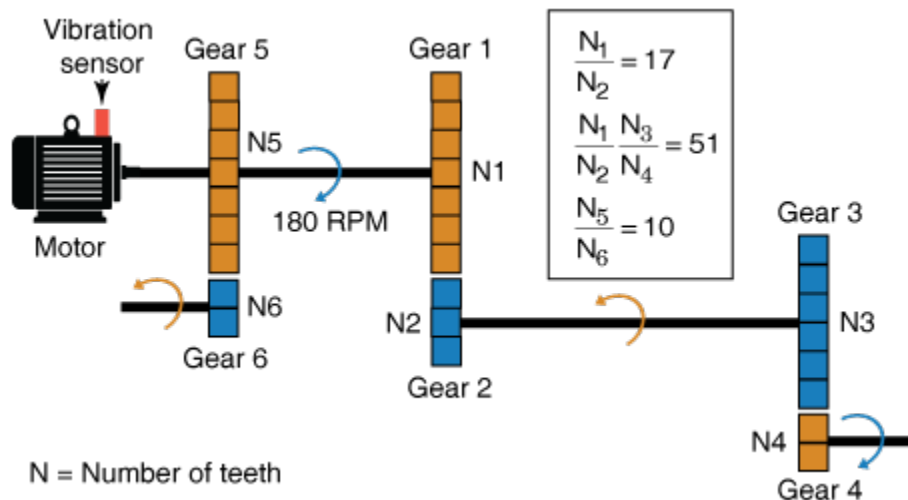
`___ = tsadifference( ___ )` allows you to specify additional parameters using one or more name-value pair arguments. You can use this syntax with any of the previous input and output arguments.

`tsadifference( ___ )` with no output arguments plots the time-domain and frequency-domain plots of the raw and difference TSA signals.

## Examples

### Find and Visualize the Difference Signal of a Compound TSA Signal

Consider a drivetrain with six gears driven by a motor that is fitted with a vibration sensor, as depicted in the figure below. Gear 1 on the motor shaft meshes with gear 2 with a gear ratio of 17:1. The final gear ratio, that is, the ratio between gears 1 and 2 and gears 3 and 4, is 51:1. Gear 5, also on the motor shaft, meshes with gear 6 with a gear ratio of 10:1. The motor is spinning at 180 RPM, and the sampling rate of the vibration sensor is 50 KHz. To obtain the signal containing just the meshing components for gears 5 and 6, filter out the components of the shaft rotation, gears 1 and 2 and, 3 and 4 by specifying their gear ratios of 17 and 51 in `orderList`. The signal components corresponding to the shaft rotation (`order = 1`) is always implicitly included in the computation.



```
rpm = 180;
fs = 50e3;
t = (0:1/fs:(1/3)-1/fs)';           % sample times
orderList = [17 51];
f = rpm/60*[1 orderList];
```

In practice, you would use measured data such as vibration signals obtained from an accelerometer. For this example, generate TSA signal  $X$ , which is the simulated data from the vibration sensor mounted on the motor.

```
X = sin(2*pi*f(1)*t) + sin(2*pi*2*f(1)*t) + ... % motor shaft rotation and harmonic
    3*sin(2*pi*f(2)*t) + 3*sin(2*pi*2*f(2)*t) + ... % gear mesh vibration and harmonic
    4*sin(2*pi*f(3)*t) + 4*sin(2*pi*2*f(3)*t) + ... % gear mesh vibration and harmonic
    2*sin(2*pi*10*f(1)*t); % gear mesh vibration for gears 5 and 6
```

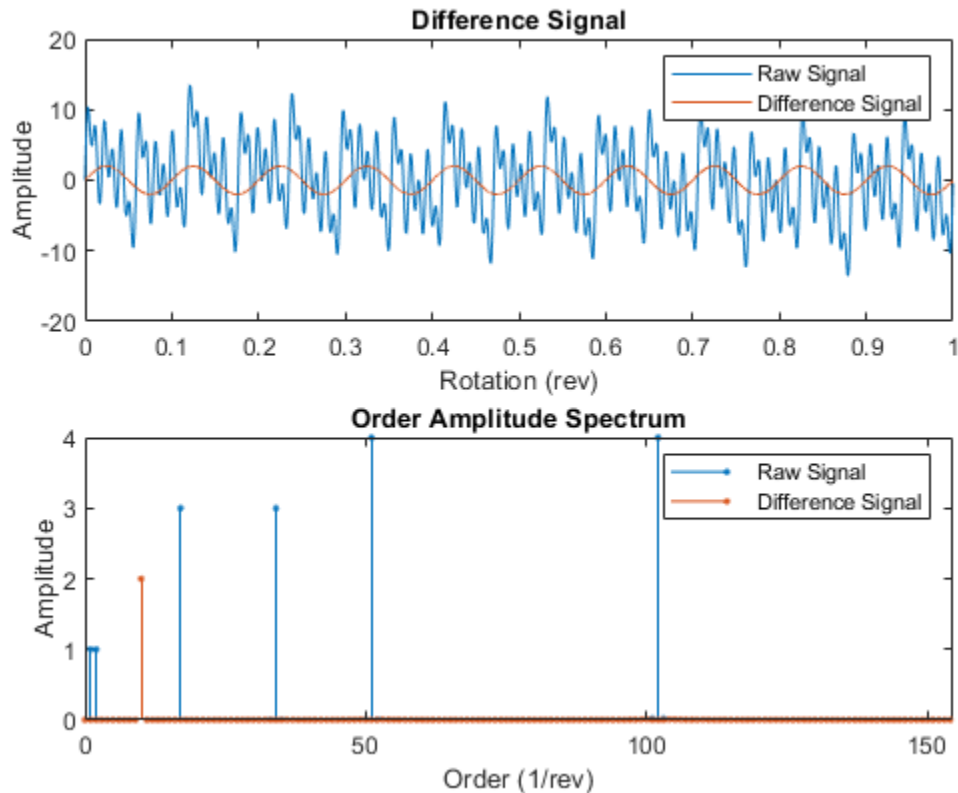
Compute the difference signal of the TSA signal using the sample time, rpm, and the mesh orders to be filtered out.

```
Y = tsadifference(X,t,rpm,orderList);
```

The output  $Y$  is a vector containing the gear mesh signal and harmonics for gears 5 and 6.

Visualize the difference signal, the raw TSA signal, and their amplitude spectrum on a plot.

```
tsadifference(X,fs,rpm,orderList)
```



From the amplitude spectrum plot, observe the following components:

- The filtered component at the 17th order and its harmonic at the 34th order
- The second filtered component at the 51st order and its harmonic at the 102nd order
- The residual mesh components for gears 5 and 6 at the 10th order
- The filtered shaft component at the 1st and 2nd orders
- The amplitudes on the spectrum plot match the amplitudes of individual signals

### Compute Difference Signal and Amplitude Spectrum of a TSA Signal

In this example, `sineWavePhaseMod.mat` contains the data of a phase modulated sine wave. `XT` is a timetable with the sine wave data and `rpm` used is 60 RPM. The sine wave has a frequency of 32 Hz. To filter out the unmodulated sine wave and the sidebands of the phase modulating signal, use 32 as the `orderList`.

Load the data and the required variables.

```
load('sineWavePhaseMod.mat','XT','rpm','orders')
head(XT,4)
```

```
ans=4x1 timetable
      Time      Data
-----
0 sec          0
0.00097656 sec 0.2011
0.0019531 sec  0.39399
0.0029297 sec  0.57078
```

Note that the time values in `XT` are strictly increasing, equidistant, and finite.

Compute the difference signal and its amplitude spectrum. Set the value of `'Domain'` to `'frequency'` since the orders are in Hz.

```
[Y,S] = tsdifference(XT,rpm,orders,'Domain','frequency')
```

```
Y=1024x1 timetable
      Time      Data
-----
0 sec          2.2849e-15
0.00097656 sec 0.046525
0.0019531 sec  0.091185
0.0029297 sec  0.13219
0.0039062 sec  0.1679
0.0048828 sec  0.19688
0.0058594 sec  0.21799
0.0068359 sec  0.23039
0.0078125 sec  0.2336
0.0087891 sec  0.22751
0.0097656 sec  0.21239
0.010742 sec   0.18888
```

```

0.011719 sec      0.15793
0.012695 sec      0.12081
0.013672 sec      0.079041
0.014648 sec      0.034303
:

```

```
S = 1024×1 complex
```

```

-0.2403 + 0.0000i
0.0000 + 0.0000i
0.0000 + 0.0000i
0.1760 + 0.0553i
0.0059 + 0.3637i
-0.0798 - 0.1911i
-0.0178 + 0.1676i
0.1227 + 0.0887i
-0.0879 - 0.1605i
0.0076 + 0.1280i
:

```

The output `Y` is a timetable that contains the difference signal, while `S` is a vector that contains the amplitude spectrum of the difference signal `Y`.

### Visualize the Difference Signal and Amplitude Spectrum of a TSA Signal

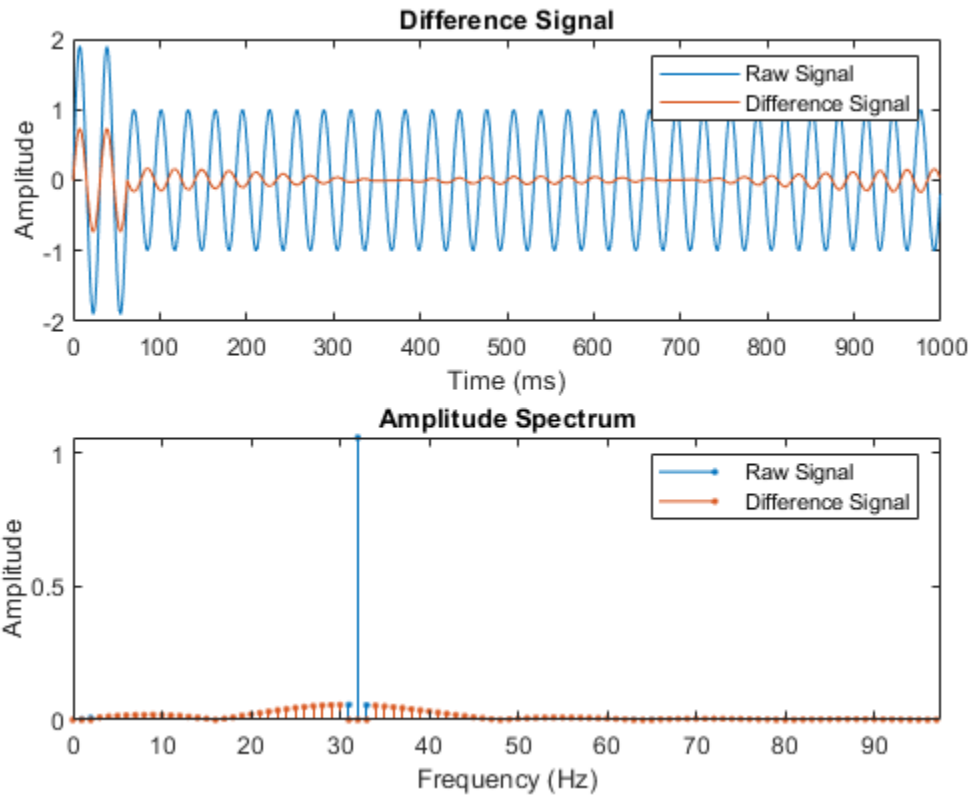
In this example, `sineWaveRectangularPulse.mat` contains the data of a sine wave modulated by a rectangular pulse. `X` is a vector with the modulated sine wave data obtained at a shaft speed of 60 RPM. The unmodulated sine wave has a frequency of 32 Hz and amplitude of 1.0 units.

Load the data, and plot the difference signal of the modulated TSA signal `X`. To obtain the difference signal, filter out the unmodulated sine wave and the sidebands of the modulation signal by specifying the frequency of 32 Hz in `orderList`. Set the value of `'Domain'` to `'frequency'`.

```

load('sineWaveRectangularPulse.mat','X','t','rpm','orderList')
tsadifference(X,t,rpm,orderList,'Domain','frequency');

```



From the plot, observe the waveform and amplitude spectrum of the difference and raw signals, respectively. Observe that the difference signal contains everything except:

- Unmodulated sine wave at 32 Hz
- First-order sidebands of the unmodulated sine wave at 31 Hz and 33 Hz, respectively

## Input Arguments

**X — Time-synchronous averaged (TSA) signal**

vector

Time-synchronous averaged (TSA) signal, specified as a vector. The time-synchronous averaged signal is computed from a long and relatively periodic raw signal through synchronization, resampling, and averaging. For more information on TSA signals, see `t sa`.

Time-synchronous averaging is a convenient method of background noise reduction in a spectrum of complex signals. It is effective in concentrating useful information that can be extracted from a time-domain signal for predictive maintenance. The synchronization typically requires a tachometer pulse signal in addition to the raw sensor data. The TSA signal depicts measurements at equally spaced angular positions over a single revolution of a shaft of interest.

### **XT — Time-synchronous averaged signal**

timetable

Time synchronous averaged (TSA) signal, specified as a timetable. XT must contain a single numeric column variable corresponding to the TSA signal. Time values in XT must be strictly increasing, equidistant, and finite.

### **fs — Sampling frequency of the TSA signal**

positive scalar

Sampling frequency of the TSA signal in Hertz, specified as a positive scalar.

### **t — Sample times of the TSA signal**

positive scalar | vector of positive values

Sample times of the TSA signal, specified as a positive scalar or a vector of positive values.

If `t` is:

- A positive scalar, it contains the time interval or duration between samples. You must specify `t` as a `duration` variable.
- A vector of positive values, it contains sample times corresponding to elements in `X`. The time values must be strictly increasing, equidistant, and finite. You can specify `t` as a `double` or `duration` variable.

### **rpm — Rotational speed of the shaft**

positive scalar

Rotational speed of the shaft, specified as a positive scalar. `tsadifference` uses a bandwidth equal to the shaft speed and the value of 'NumSidebands' around the

frequencies of interest to compute  $Y$  from the TSA signal. Specify `rpm` in revolutions per minute. The signal components corresponding to this frequency, that is, `order = 1` are always filtered out.

## **orderList — Orders to be filtered out of the TSA signal**

vector of positive integers

Orders to be filtered out of the TSA signal, specified as a vector of positive integers. Select the orders and harmonics to be filtered out of the TSA signal by observing them on the amplitude spectrum plot. For instance, specify `orderList` as the known mesh orders in a gear train to filter out the known components and their harmonics. For more information, see “Visualize the Difference Signal and Amplitude Spectrum of a TSA Signal” on page 1-193. Specify the units of `orderList` by selecting the appropriate value for 'Domain'.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, ..., NameN, ValueN`.

Example: `..., 'NumSidebands', 2`

## **NumSidebands — Number of sidebands to be filtered from the orderList frequencies and their harmonics**

0 (default) | nonnegative integer

Number of sidebands to be filtered from the `orderList` frequencies and their harmonics, specified as the comma-separated pair consisting of 'NumSidebands' and a nonnegative integer. The width of sidebands is determined using  $2 * (\text{rpm}/60) * (\text{NumSidebands} + 0.5)$ . Modify 'NumSidebands' based on the number of sidebands to be filtered from  $X$  as observed in the amplitude spectrum plot.

## **NumRotations — Number of shaft rotations in the TSA signal**

1 (default) | positive integer

Number of shaft rotations in the TSA signal, specified as the comma-separated pair consisting of 'NumRotations' and a positive integer. Modify 'NumRotations' if your input  $X$  or  $XT$  contains data for more than one rotation of the driver gear shaft. The function uses 'NumRotations' to determine the number of rotations to be shown on the x-axis of the plot. The filtering results in  $Y$  are not affected by this value.



**Domain — Units of the orderList values**

'order' (default) | 'frequency'

Units of the `orderList` values, specified as the comma-separated pair consisting of 'Domain' and one of the following:

- 'frequency', if the orders in `orderList` are specified as frequencies in units of Hertz.
- 'order', if the orders in `orderList` are specified as number of rotations relative to the value of `rpm`. For example, if the rotational speed of the driven gear is defined as a factor of the driver gear `rpm`, specify 'Domain' as 'order'. Also, choose 'order' if you are comparing data obtained from machines operating at different speeds.

**Output Arguments****Y — Difference signal of the TSA signal**

vector | timetable

Difference signal of the TSA signal, returned as:

- A vector, when the TSA signal is specified as a vector `X`.
- A timetable, when the TSA signal is specified as a timetable `XT`.

The difference signal is computed by removing the residual signal, the first-order sidebands, the value of 'NumSidebands', and their respective harmonics from `X`. You can use `Y` to further extract condition indicators of rotating machinery for predictive maintenance. For example, extracting the FM4 indicator from `Y` is useful to detect faults isolated to only a limited number of teeth in a gear mesh. For more information on how `Y` is computed, see “Algorithms” on page 1-198.

For more information on residual signal, see `tsaresidual`.

**S — Amplitude spectrum of the difference signal**

vector

Amplitude spectrum of the difference signal, returned as a vector. `S` is the normalized fast Fourier transform of the signal `Y`. `S` is the same length as the input TSA signal `X`. For more information on how `S` is computed, see “Algorithms” on page 1-198.

## Algorithms

### Difference Signal

The difference signal is computed from the TSA signal by filtering the following from the signal spectrum:

- Shaft frequency and its harmonics
- Gear meshing frequencies and their harmonics
- First-order sidebands at the gear meshing frequencies and their harmonics
- Optionally, the sidebands specified in 'NumSidebands' at the gear meshing frequencies and their harmonics

`tsadifference` uses a bandwidth equal to three times the shaft speed and the value of 'NumSidebands', around the frequencies of interest, to compute  $Y$  from the TSA signal.

### Amplitude Spectrum

The amplitude spectrum of the difference signal is computed as follows,

$$S = \frac{fft(Y)}{length(Y) * 2}$$

Here,  $Y$  is the difference signal.

## References

- [1] McFadden, P.D. "Examination of a Technique for the Early Detection of Failure in Gears by Signal Processing of the Time Domain Average of the Meshing Vibration." *Aero Propulsion Technical Memorandum 434*. Melbourne, Australia: Aeronautical Research Laboratories, Apr. 1986.
- [2] Večeř, P., Marcel Kreidl, and R. Šmíd. "Condition Indicators for Gearbox Monitoring Systems." *Acta Polytechnica* 45.6 (2005), pages 35-43.
- [3] Zakrajsek, J. J., Townsend, D. P., and Decker, H. J. "An Analysis of Gear Fault Detection Methods as Applied to Pitting Fatigue Failure Data." *Technical Memorandum 105950*. NASA, Apr. 1993.

[4] Zakrajsek, James J. "An investigation of gear mesh failure prediction techniques."  
National Aeronautics and Space Administration Cleveland OH Lewis Research  
Center, 1989. No. NASA-E-5049.

## **See Also**

tsaregular | tsaresidual

**Introduced in R2018b**

## tsaregular

Regular signal of a time-synchronous averaged signal

### Syntax

```
Y = tsaregular(X,fs,rpm,orderList)
Y = tsaregular(X,t,rpm,orderList)
Y = tsaregular(XT,rpm,orderList)
[Y,S] = tsaregular(____)
____ = tsaregular(____,Name,Value)

tsaregular(____)
```

### Description

`Y = tsaregular(X,fs,rpm,orderList)` computes the regular signal `Y` of the time-synchronous averaged (TSA) signal vector `X` using sampling rate `fs`, the rotational speed `rpm`, and the orders to be retained `orderList`. `Y` is computed by retaining the primary frequency, the components in `orderList`, and their respective harmonics from `X`. You can use `Y` to further extract condition indicators of rotating machinery for predictive maintenance. For example, extracting the FM0 indicator from `Y` is useful in identifying major changes such as gear tooth breakage or heavy wear in a gear box.

`Y = tsaregular(X,t,rpm,orderList)` computes the regular signal `Y` of the TSA signal vector `X` with corresponding time values from `t`.

`Y = tsaregular(XT,rpm,orderList)` computes the regular signal `Y` of the TSA signal stored in the timetable `XT`. `XT` must contain a single numeric column variable.

`[Y,S] = tsaregular(____)` returns the amplitude spectrum `S` of the regular signal `Y`. `S` is the amplitude spectrum computed using the normalized fast Fourier transform (FFT) of `Y`.

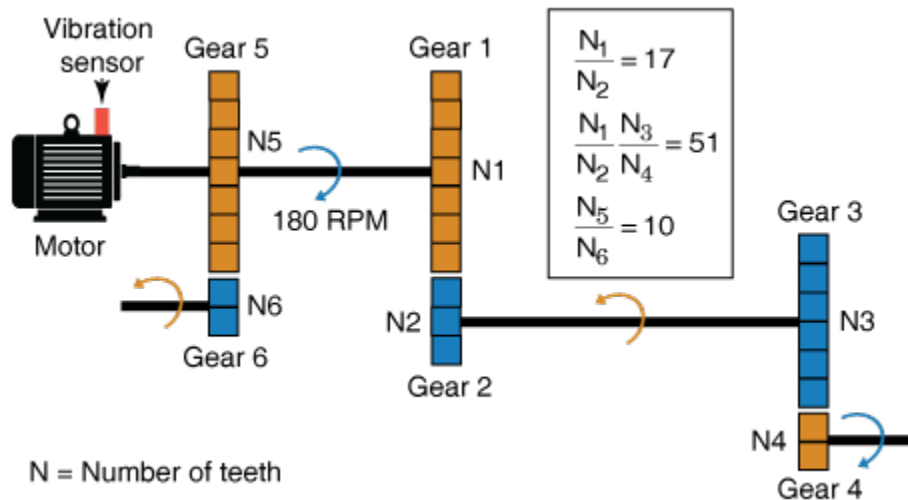
`____ = tsaregular(____,Name,Value)` allows you to specify additional parameters using one or more name-value pair arguments. You can use this syntax with any of the previous input and output arguments.

tsaregular( \_\_\_ ) with no output arguments plots the time-domain and frequency-domain plots of the raw and regular TSA signals.

## Examples

### Find and Visualize the Regular Signal of a Compound TSA Signal

Consider a drivetrain with six gears driven by a motor that is fitted with a vibration sensor, as depicted in the figure below. Gear 1 on the motor shaft meshes with gear 2 with a gear ratio of 17:1. The final gear ratio, that is, the ratio between gears 1 and 2 and gears 3 and 4, is 51:1. Gear 5, also on the motor shaft, meshes with gear 6 with a gear ratio of 10:1. The motor is spinning at 180 RPM, and the sampling rate of the vibration sensor is 50 KHz. To retain the signal containing the meshing components of the gears 1 and 2, gears 3 and 4 and, the shaft rotation, specify their gear ratios of 17 and 51 in orderList. The signal components corresponding to the shaft rotation (order = 1) is always implicitly included in the computation.



```
rpm = 180;
fs = 50e3;
t = (0:1/fs:(1/3)-1/fs)';
orderList = [17 51];
f = rpm/60*[1 orderList];
```

% sample times

In practice, you would use measured data such as vibration signals obtained from an accelerometer. For this example, generate TSA signal  $X$ , which is the simulated data from the vibration sensor mounted on the motor.

```
X = sin(2*pi*f(1)*t) + sin(2*pi*2*f(1)*t) + ... % motor shaft rotation and harmonic
    3*sin(2*pi*f(2)*t) + 3*sin(2*pi*2*f(2)*t) + ... % gear mesh vibration and harmonic
    4*sin(2*pi*f(3)*t) + 4*sin(2*pi*2*f(3)*t) + ... % gear mesh vibration and harmonic
    2*sin(2*pi*10*f(1)*t); % gear mesh vibration for gears 5 and 6
```

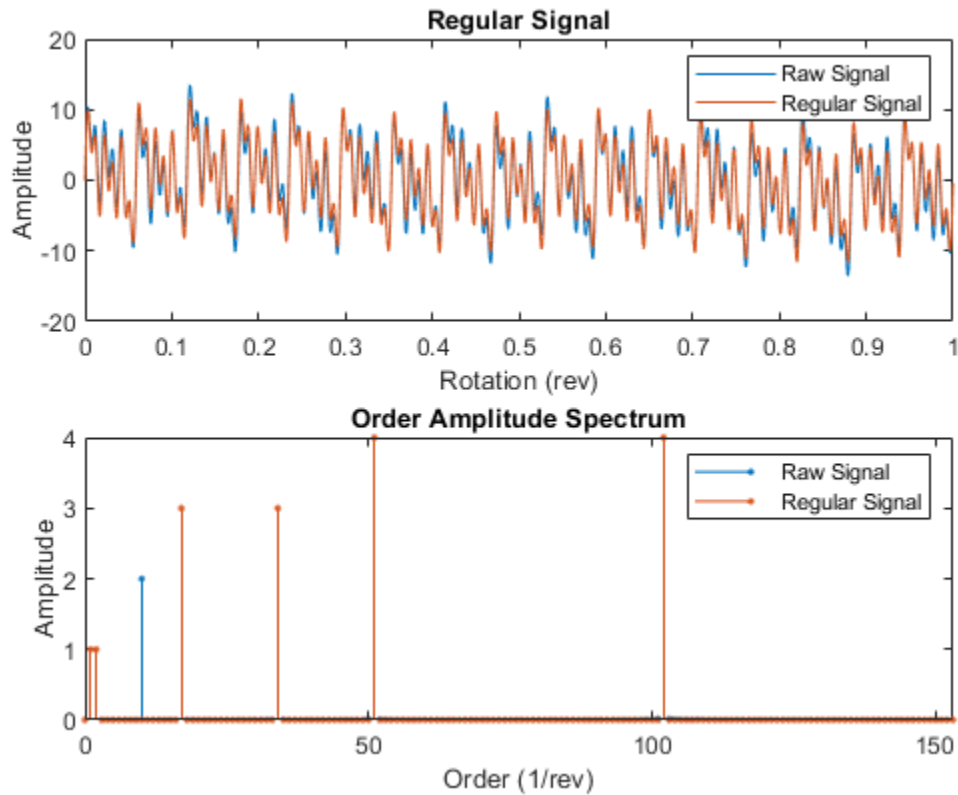
Compute the regular signal of the TSA signal using the sample time, rpm, and the mesh orders to be retained.

```
Y = tsaregular(X,t,rpm,orderList);
```

The output  $Y$  is a vector containing everything except the gear mesh signal and harmonics for gears 5 and 6.

Visualize the regular signal, the raw TSA signal, and their amplitude spectrum on a plot.

```
tsaregular(X,fs,rpm,orderList)
```



From the amplitude spectrum plot, observe the following components:

- The retained component at the 17th order and its harmonic at the 34th order
- The second retained component at the 51st order and its harmonic at the 102nd order
- The filtered mesh components for gears 5 and 6 at the 10th order
- The retained shaft component at the 1st and 2nd orders
- The amplitudes on the spectrum plot match the amplitudes of individual signals

### Compute Regular Signal and Amplitude Spectrum of a TSA Signal

In this example, `sineWavePhaseMod.mat` contains the data of a phase modulated sine wave. `XT` is a timetable with the sine wave data and `rpm` used is 60 RPM. The sine wave has a frequency of 32 Hz and to recover the unmodulated sine wave, use 32 as the `orderList`.

Load the data and the required variables.

```
load('sineWavePhaseMod.mat','XT','rpm','orders')
head(XT,4)
```

```
ans=4x1 timetable
      Time      Data
-----
0 sec          0
0.00097656 sec 0.2011
0.0019531 sec  0.39399
0.0029297 sec  0.57078
```

Note that the time values in `XT` are strictly increasing, equidistant, and finite.

Compute the regular signal and its amplitude spectrum. Set the value of `'Domain'` to `'frequency'` since the orders are in Hz.

```
[Y,S] = tsaregular(XT,rpm,orders,'Domain','frequency')
```

```
Y=1024x1 timetable
      Time      Data
-----
0 sec          -2.552e-15
0.00097656 sec 0.14928
0.0019531 sec  0.29283
0.0029297 sec  0.42512
0.0039062 sec  0.54108
0.0048828 sec  0.63624
0.0058594 sec  0.70695
0.0068359 sec  0.75049
0.0078125 sec   0.7652
0.0087891 sec  0.75049
0.0097656 sec  0.70695
0.010742 sec   0.63624
```



```

0.011719 sec      0.54108
0.012695 sec      0.42512
0.013672 sec      0.29283
0.014648 sec      0.14928
:

```

*S = 1024×1 complex*

```

0.0201 + 0.0000i
0.0964 - 0.1714i
0.2640 + 0.0958i
0.0021 + 0.0018i
-0.0002 - 0.0044i
-0.0002 - 0.0036i
-0.0003 - 0.0030i
-0.0024 + 0.0074i
0.0103 + 0.0031i
-0.0048 - 0.0008i
:

```

The output *Y* is a timetable that contains the regular signal, that is, the unmodulated sine wave, while *S* is a vector that contains the amplitude spectrum of the regular signal *Y*.

### Visualize the Regular Signal and Amplitude Spectrum of a TSA Signal

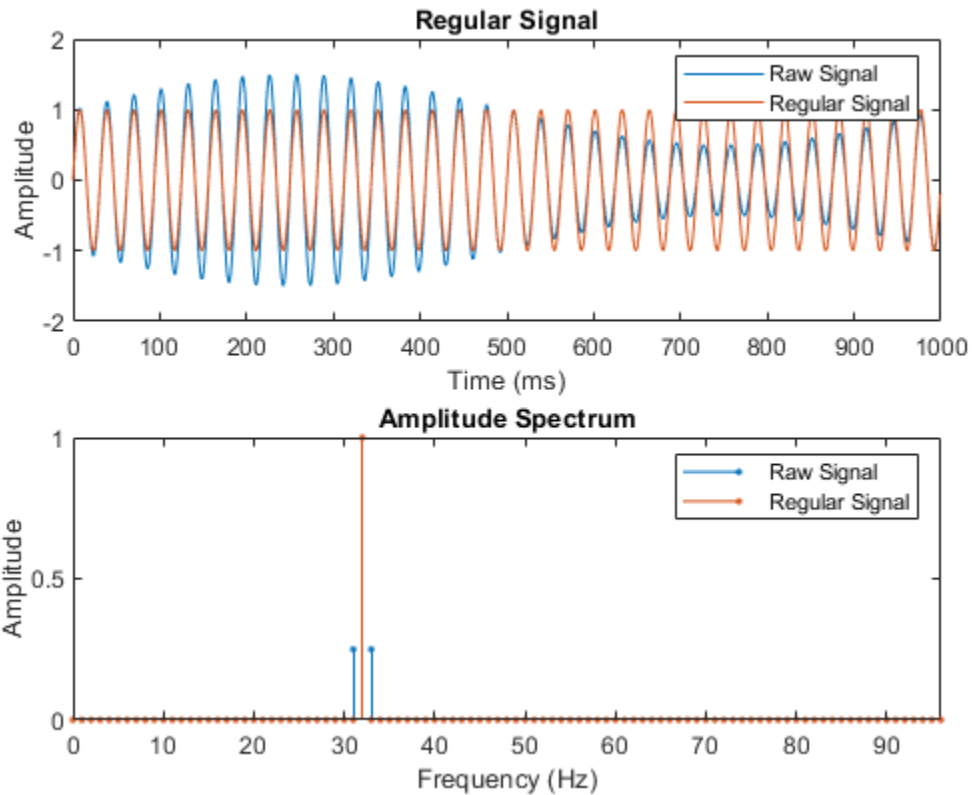
In this example, `sineWaveAmpMod.mat` contains the data of an amplitude modulated sine wave. *X* is a vector with the amplitude modulated sine wave data obtained at a shaft speed of 60 RPM. The unmodulated sine wave has a frequency of 32 Hz and amplitude of 1.0 units.

Load the data, and plot the regular signal of the amplitude modulated TSA signal *X*. To retain the unmodulated signal, specify the frequency of 32 Hz in `orderList`. Set the value of `'Domain'` to `'frequency'`.

```

load('sineWaveAmpMod.mat','X','t','rpm','orderList')
tsaregular(X,t,rpm,orderList,'Domain','frequency');

```



From the plot, observe the waveform and amplitude spectrum of the regular and raw signals, respectively. Observe that the regular signal contains the unmodulated sine wave with an amplitude of 1.0 units and frequency of 32 Hz.

## Input Arguments

### X — Time-synchronous averaged (TSA) signal

vector

Time-synchronous averaged (TSA) signal, specified as a vector. The time-synchronous averaged signal is computed from a long and relatively periodic raw signal through

synchronization, resampling, and averaging. For more information on TSA signals, see `tSa`.

Time-synchronous averaging is a convenient method of background noise reduction in a spectrum of complex signals. It is effective in concentrating useful information that can be extracted from a time-domain signal for predictive maintenance. The synchronization typically requires a tachometer pulse signal in addition to the raw sensor data. The TSA signal depicts measurements at equally spaced angular positions over a single revolution of a shaft of interest.

### **XT — Time-synchronous averaged signal**

timetable

Time synchronous averaged (TSA) signal, specified as a timetable. XT must contain a single numeric column variable corresponding to the TSA signal. Time values in XT must be strictly increasing, equidistant, and finite.

### **fs — Sampling frequency of the TSA signal**

positive scalar

Sampling frequency of the TSA signal in Hertz, specified as a positive scalar.

### **t — Sample times of the TSA signal**

positive scalar | vector of positive values

Sample times of the TSA signal, specified as a positive scalar or a vector of positive values.

If `t` is:

- A positive scalar, it contains the time interval or duration between samples. You must specify `t` as a `duration` variable.
- A vector of positive values, it contains sample times corresponding to elements in `X`. The time values must be strictly increasing, equidistant, and finite. You can specify `t` as a `double` or `duration` variable.

### **rpm — Rotational speed of the shaft**

positive scalar

Rotational speed of the shaft, specified as a positive scalar. `tsaregular` uses a bandwidth equal to the shaft speed and the value of `'NumSidebands'` around the frequencies of interest to compute `Y` from the TSA signal. Specify `rpm` in revolutions per

minute. The signal components corresponding to this frequency, that is, `order = 1` are always retained.

## **orderList — Orders to be retained from the TSA signal**

vector of positive integers

Orders to be retained from the TSA signal, specified as a vector of positive integers. Select the orders and harmonics to be retained from the TSA signal by observing them on the amplitude spectrum plot. For instance, specify `orderList` as the known mesh orders in a gear train to retain the desired components and their harmonics. For more information, see “Find and Visualize the Regular Signal of a Compound TSA Signal” on page 1-201. Specify the units of `orderList` by selecting the appropriate value for 'Domain'.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, . . . , NameN, ValueN`.

Example: `... , 'NumSidebands', 2`

## **NumHarmonics — Number of shaft and gear meshing frequency harmonics to be filtered**

2 (default) | positive integer

Number of shaft and gear meshing frequency harmonics to be filtered, specified as the comma-separated pair consisting of 'NumHarmonics' and a positive integer. Modify 'NumHarmonics' if your TSA signal contains more than two known harmonics of components to be filtered.

## **NumSidebands — Number of sidebands to be retained from the orderList frequencies and their harmonics**

0 (default) | nonnegative integer

Number of sidebands to be retained from the `orderList` frequencies and their harmonics, specified as the comma-separated pair consisting of 'NumSidebands' and a nonnegative integer. The width of sidebands is determined using  $2 * (\text{rpm} / 60) * (\text{NumSidebands} + 0.5)$ . Modify 'NumSidebands' based on the number of sidebands to be retained from `X` as observed in the amplitude spectrum plot.

**NumRotations — Number of shaft rotations in the TSA signal**

1 (default) | positive integer

Number of shaft rotations in the TSA signal, specified as the comma-separated pair consisting of 'NumRotations' and a positive integer. Modify 'NumRotations' if your input X or XT contains data for more than one rotation of the driver gear shaft. The function uses 'NumRotations' to determine the number of rotations to be shown on the x-axis of the plot. The filtering results in Y are not affected by this value.

**Domain — Units of the orderList values**

'order' (default) | 'frequency'

Units of the orderList values, specified as the comma-separated pair consisting of 'Domain' and one of the following:

- 'frequency', if the orders in orderList are specified as frequencies in units of Hertz.
- 'order', if the orders in orderList are specified as number of rotations relative to the value of rpm. For example, if the rotational speed of the driven gear is defined as a factor of the driver gear rpm, specify 'Domain' as 'order'. Also, choose 'order' if you are comparing data obtained from machines operating at different speeds.

## Output Arguments

**Y — Regular signal of the TSA signal**

vector | timetable

Regular signal of the TSA signal, returned as:

- A vector, when the TSA signal is specified as a vector X.
- A timetable, when the TSA signal is specified as a timetable XT.

Y is computed by retaining the primary frequency, the components in orderList, the first-order sidebands in 'NumSidebands', and their respective harmonics from X. You can use Y to further extract condition indicators of rotating machinery for predictive maintenance. For example, extracting the FM0 indicator from Y is useful in identifying major changes such as gear tooth breakage or heavy wear in a gear box. For more information on how Y is computed, see “Algorithms” on page 1-210.

## **S — Amplitude spectrum of the regular signal**

vector

Amplitude spectrum of the regular signal, returned as a vector. S is the normalized fast Fourier transform of the signal Y. S is the same length as the input TSA signal X. For more information on how S is computed, see “Algorithms” on page 1-210.

## **Algorithms**

### **Regular Signal**

The regular signal is computed from the TSA signal by retaining the following from the signal spectrum:

- Shaft frequency and its harmonics
- Gear meshing frequencies and their harmonics
- Optionally, the sidebands specified in 'NumSidebands' at the gear meshing frequencies and their harmonics

`tsaregular` uses a bandwidth equal to the shaft speed times the value of 'NumSidebands', around the frequencies of interest, to compute Y from the TSA signal. The regular signal is related to the residual signal through the equation

$Y_{regular} = X - Y_{residual}$ . If the first-order sidebands are retained in the regular signal, then,  $Y_{regular} = X - Y_{difference}$ .

### **Amplitude Spectrum**

The amplitude spectrum of the regular signal is computed as follows,

$$S = \frac{fft(Y)}{length(Y) * 2}$$

Here, Y is the regular signal.

## **References**

- [1] McFadden, P.D. "Examination of a Technique for the Early Detection of Failure in Gears by Signal Processing of the Time Domain Average of the Meshing

Vibration." *Aero Propulsion Technical Memorandum 434*. Melbourne, Australia: Aeronautical Research Laboratories, Apr. 1986.

[2] Večeř, P., Marcel Kreidl, and R. Šmíd. "Condition Indicators for Gearbox Monitoring Systems." *Acta Polytechnica* 45.6 (2005), pages 35-43.

[3] Zakrajsek, J. J., Townsend, D. P., and Decker, H. J. "An Analysis of Gear Fault Detection Methods as Applied to Pitting Fatigue Failure Data." *Technical Memorandum 105950*. NASA, Apr. 1993.

[4] Zakrajsek, James J. "An investigation of gear mesh failure prediction techniques." National Aeronautics and Space Administration Cleveland OH Lewis Research Center, 1989. No. NASA-E-5049.

## See Also

tsadifference | tsaresidual

**Introduced in R2018b**

## tsaresidual

Residual signal of a time-synchronous averaged signal

### Syntax

```
Y = tsaresidual(X,fs,rpm,orderList)
Y = tsaresidual(X,t,rpm,orderList)
Y = tsaresidual(XT,rpm,orderList)
[Y,S] = tsaresidual(____)
____ = tsaresidual(____,Name,Value)

tsaresidual(____)
```

### Description

`Y = tsaresidual(X,fs,rpm,orderList)` computes the residual signal `Y` of the time-synchronous averaged (TSA) signal vector `X` using sampling rate `fs`, the rotational speed `rpm`, and the orders to be filtered `orderList`. The residual signal is computed by removing the components in `orderList` and their harmonics from `X`. You can use `Y` to further extract condition indicators of rotating machinery for predictive maintenance. For example, extracting the root-mean-squared value of the residual signal is useful in identifying changes over time which indicate potential machine faults.

`Y = tsaresidual(X,t,rpm,orderList)` computes the residual signal `Y` of the TSA signal vector `X` with corresponding time values in vector `t`.

`Y = tsaresidual(XT,rpm,orderList)` computes the residual signal `Y` of the TSA signal stored in the timetable `XT`. `XT` must contain a single numeric column variable.

`[Y,S] = tsaresidual(____)` returns the amplitude spectrum `S` of the residual signal `Y`. `S` is the amplitude spectrum computed using the normalized fast Fourier transform (FFT) of `Y`.

`____ = tsaresidual(____,Name,Value)` allows you to specify additional parameters using one or more name-value pair arguments. You can use this syntax with any of the previous input and output arguments.

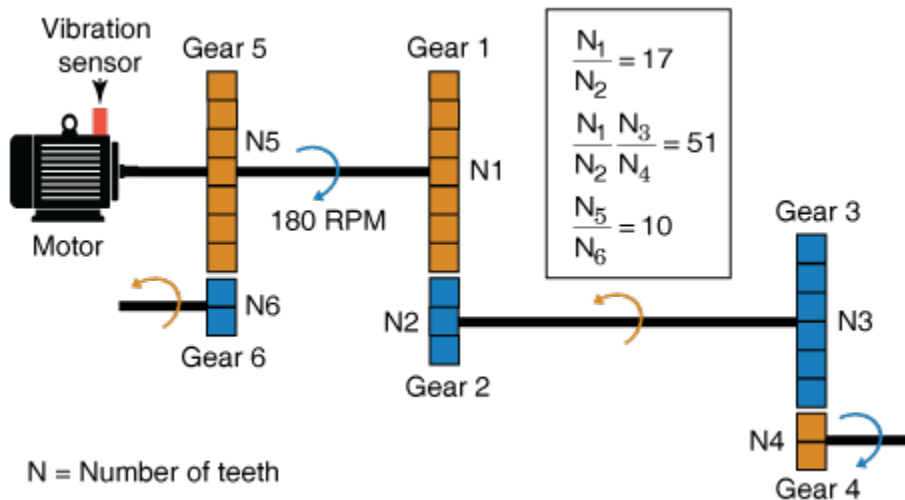


tsaresidual( \_\_\_ ) with no output arguments plots the time-domain and frequency-domain plots of the raw and residual TSA signals.

## Examples

### Find and Visualize the Residual Signal of a Compound TSA Signal

Consider a drivetrain with six gears driven by a motor that is fitted with a vibration sensor, as depicted in the figure below. Gear 1 on the motor shaft meshes with gear 2 with a gear ratio of 17:1. The final gear ratio, that is, the ratio between gears 1 and 2 and gears 3 and 4, is 51:1. Gear 5, also on the motor shaft, meshes with gear 6 with a gear ratio of 10:1. The motor is spinning at 180 RPM, and the sampling rate of the vibration sensor is 50 KHz. To obtain the signal containing just the meshing components for gears 5 and 6, filter out the signal components due to the gears 1 and 2 and, 3 and 4 by specifying their gear ratios of 17 and 51 in orderList. The signal components corresponding to the shaft rotation (order = 1) is always implicitly included in the computation.



```
rpm = 180;
fs = 50e3;
t = (0:1/fs:(1/3)-1/fs)';
orderList = [17 51];
f = rpm/60*[1 orderList];
```

% sample times

In practice, you would use measured data such as vibration signals obtained from an accelerometer. For this example, generate TSA signal  $X$ , which is the simulated data from the vibration sensor mounted on the motor.

```
X = sin(2*pi*f(1)*t) + sin(2*pi*2*f(1)*t) + ... % motor shaft rotation and harmonic
    3*sin(2*pi*f(2)*t) + 3*sin(2*pi*2*f(2)*t) + ... % gear mesh vibration and harmonic
    4*sin(2*pi*f(3)*t) + 4*sin(2*pi*2*f(3)*t) + ... % gear mesh vibration and harmonic
    2*sin(2*pi*10*f(1)*t); % gear mesh vibration for gears 5 and 6
```

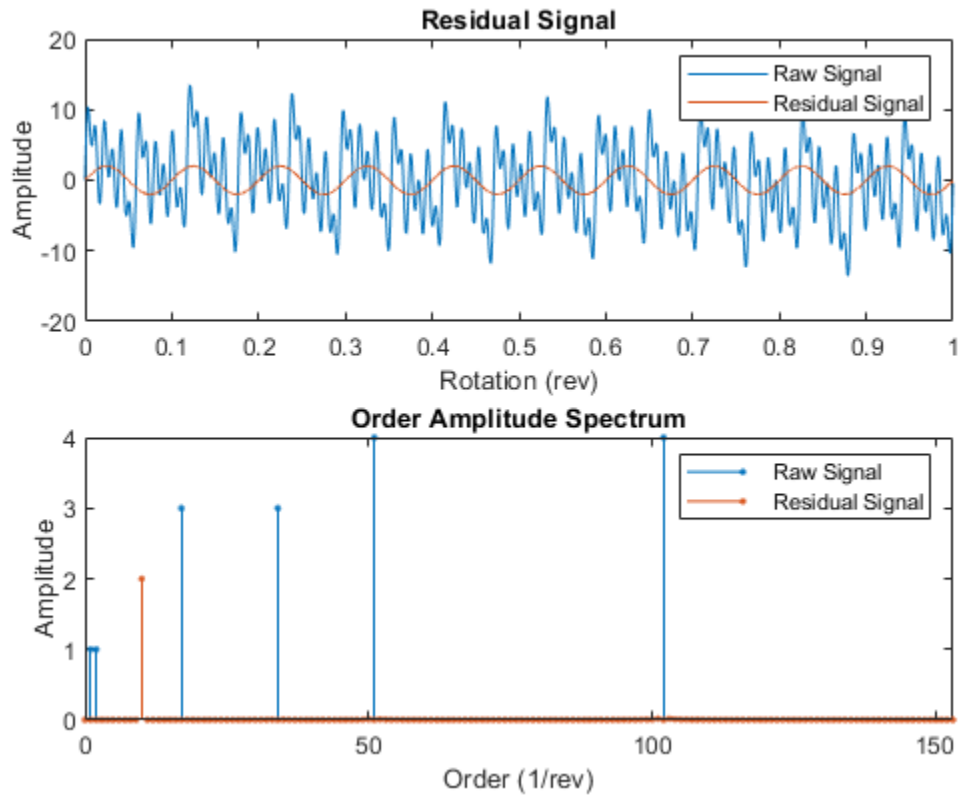
Compute the residual of the TSA signal using the sample time, rpm, and the mesh orders to be filtered out.

```
Y = tsaresidual(X,t,rpm,orderList);
```

The output  $Y$  is a vector containing the gear mesh signal and harmonics for gears 5 and 6.

Visualize the residual signal, the raw TSA signal, and their amplitude spectrum on a plot.

```
tsaresidual(X,fs,rpm,orderList)
```



From the amplitude spectrum plot, observe the following components:

- The filtered component at the 17th order and its harmonic at the 34th order
- The second filtered component at the 51st order and its harmonic at the 102nd order
- The residual mesh components for gears 5 and 6 at the 10th order
- The filtered shaft component at the 1st and 2nd orders
- The amplitudes on the spectrum plot match the amplitudes of individual signals

### Compute Residual Signal and Amplitude Spectrum of a TSA Signal

In this example, `sineWavePhaseMod.mat` contains the data of a phase modulated sine wave. `XT` is a timetable with the sine wave data and `rpm` used is 60 RPM. The sine wave has a frequency of 32 Hz, and to filter out the unmodulated sine wave, use 32 as the `orderList`.

Load the data and the required variables.

```
load('sineWavePhaseMod.mat','XT','rpm','orders')
head(XT,4)
```

```
ans=4x1 timetable
      Time          Data
-----
0 sec          0
0.00097656 sec 0.2011
0.0019531 sec  0.39399
0.0029297 sec  0.57078
```

Note that the time values in `XT` are strictly increasing, equidistant, and finite.

Compute the residual signal and its amplitude spectrum. Set the value of 'Domain' to 'frequency' since the orders are in Hz.

```
[Y,S] = tsaresidual(XT,rpm,orders,'Domain','frequency')
```

```
Y=1024x1 timetable
      Time          Data
-----
0 sec          2.552e-15
0.00097656 sec 0.051822
0.0019531 sec  0.10116
0.0029297 sec  0.14566
0.0039062 sec  0.18317
0.0048828 sec  0.21188
0.0058594 sec  0.23039
0.0068359 sec  0.23776
0.0078125 sec  0.2336
0.0087891 sec  0.21803
0.0097656 sec  0.19174
0.010742 sec   0.1559
```

```

0.011719 sec      0.11215
0.012695 sec      0.062503
0.013672 sec      0.0092782
0.014648 sec      -0.045032
:

```

*S = 1024×1 complex*

```

-0.2403 + 0.0000i
0.0000 + 0.0000i
0.0000 + 0.0000i
0.1760 + 0.0553i
0.0059 + 0.3637i
-0.0798 - 0.1911i
-0.0178 + 0.1676i
0.1227 + 0.0887i
-0.0879 - 0.1605i
0.0076 + 0.1280i
:

```

The output *Y* is a timetable that contains the residual signal, that is, the phase modulation signal, while *S* is a vector that contains the amplitude spectrum of the residual signal *Y*.

### Visualize the Residual and Amplitude Spectrum of a TSA Signal

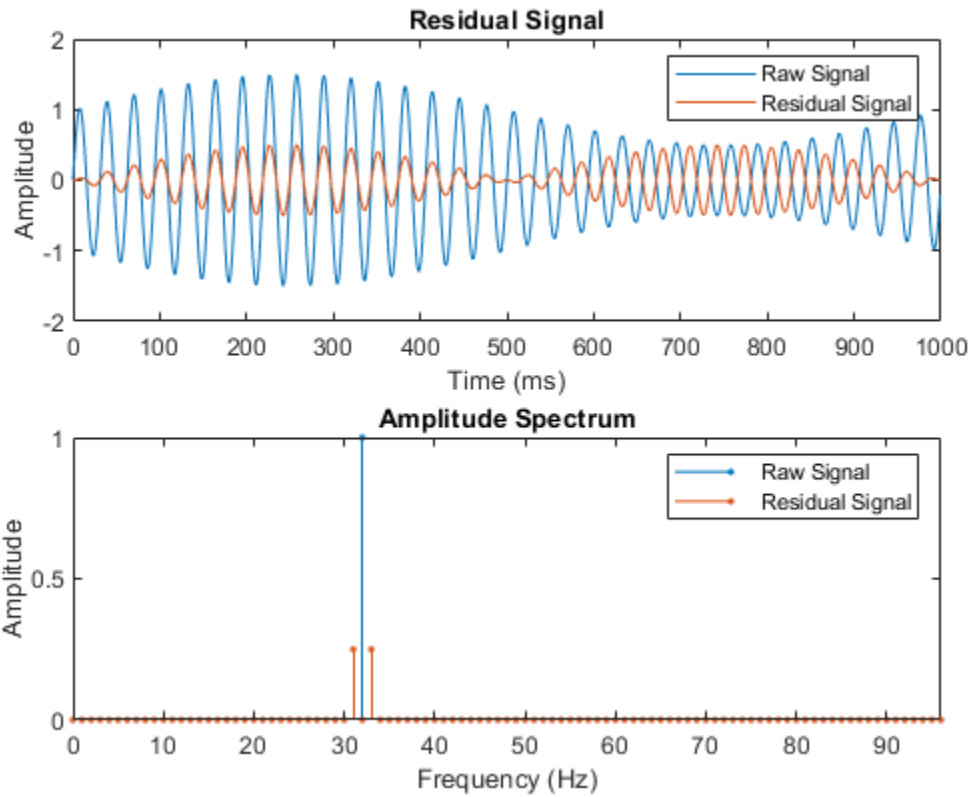
In this example, `sineWaveAmpMod.mat` contains the data of an amplitude modulated sine wave. *X* is a vector with the amplitude modulated sine wave data obtained at a shaft speed of 60 RPM. The unmodulated sine wave has a frequency of 32 Hz and amplitude of 1.0 units.

Load the data, and plot the residual signal of the amplitude modulated TSA signal *X*. To obtain the residual signal, filter out the unmodulated sine wave by specifying the frequency of 32 Hz in `orderList`. Set the value of `'Domain'` to `'frequency'`.

```

load('sineWaveAmpMod.mat','X','t','rpm','orderList')
tsaresidual(X,t,rpm,orderList,'Domain','frequency');

```



From the plot, observe the waveform and amplitude spectrum of the residual and raw signals, respectively.

## Input Arguments

### **X** — Time-synchronous averaged (TSA) signal

vector

Time-synchronous averaged (TSA) signal, specified as a vector. The time-synchronous averaged signal is computed from a long and relatively periodic raw signal through

synchronization, resampling, and averaging. For more information on TSA signals, see `t sa`.

Time-synchronous averaging is a convenient method of background noise reduction in a spectrum of complex signals. It is effective in concentrating useful information that can be extracted from a time-domain signal for predictive maintenance. The synchronization typically requires a tachometer pulse signal in addition to the raw sensor data. The TSA signal depicts measurements at equally spaced angular positions over a single revolution of a shaft of interest.

### **XT — Time-synchronous averaged signal**

`timetable`

Time synchronous averaged (TSA) signal, specified as a `timetable`. `XT` must contain a single numeric column variable corresponding to the TSA signal. Time values in `XT` must be strictly increasing, equidistant, and finite.

### **fs — Sampling frequency of the TSA signal**

`positive scalar`

Sampling frequency of the TSA signal in Hertz, specified as a positive scalar.

### **t — Sample times of the TSA signal**

`positive scalar` | `vector of positive values`

Sample times of the TSA signal, specified as a positive scalar or a vector of positive values.

If `t` is:

- A positive scalar, it contains the time interval or duration between samples. You must specify `t` as a `duration` variable.
- A vector of positive values, it contains sample times corresponding to elements in `X`. The time values must be strictly increasing, equidistant, and finite. You can specify `t` as a `double` or `duration` variable.

### **rpm — Rotational speed of the shaft**

`positive scalar`

Rotational speed of the shaft, specified as a positive scalar. `tsaresidual` uses a bandwidth equal to the shaft speed around the frequencies of interest to filter out the

undesired frequency components from the TSA signal. The signal components corresponding to this frequency, that is, `order = 1` are always filtered out.

Specify `rpm` in revolutions per minute.

### **orderList — Orders to be filtered out of the TSA signal**

vector of positive integers

Orders to be filtered out of the TSA signal, specified as a vector of positive integers. Select the orders and harmonics to be filtered out of the TSA signal by observing them on the amplitude spectrum plot. For instance, specify `orderList` as the known mesh orders in a gear train to filter out the known components and their harmonics. For more information, see “Find and Visualize the Residual Signal of a Compound TSA Signal” on page 1-213. Specify the units of `orderList` by selecting the appropriate value for 'Domain'.

## **Name-Value Pair Arguments**

Specify optional comma-separated pairs of `Name`, `Value` arguments. `Name` is the argument name and `Value` is the corresponding value. `Name` must appear inside quotes. You can specify several name and value pair arguments in any order as `Name1, Value1, . . . , NameN, ValueN`.

Example: `..., 'NumRotations', 5`

### **NumHarmonics — Number of shaft and gear meshing frequency harmonics to be filtered**

2 (default) | positive integer

Number of shaft and gear meshing frequency harmonics to be filtered, specified as the comma-separated pair consisting of 'NumHarmonics' and a positive integer. Modify 'NumHarmonics' if your TSA signal contains more than two known harmonics of components to be filtered.

### **NumRotations — Number of shaft rotations in the TSA signal**

1 (default) | positive integer

Number of shaft rotations in the TSA signal, specified as the comma-separated pair consisting of 'NumRotations' and a positive integer. Modify 'NumRotations' if your input `X` or `XT` contains data for more than one rotation of the driver gear shaft. The function uses 'NumRotations' to determine the number of rotations to be shown on the x-axis of the plot. The filtering results in `Y` are not affected by this value.



### **Domain — Units of the orderList values**

'order' (default) | 'frequency'

Units of the `orderList` values, specified as the comma-separated pair consisting of 'Domain' and one of the following:

- 'frequency', if the orders in `orderList` are specified as frequencies in units of Hertz.
- 'order', if the orders in `orderList` are specified as number of rotations relative to the value of rpm. For example, if the rotational speed of the driven gear is defined as a factor of the driver gear rpm, specify 'Domain' as 'order'. Also, choose 'order' if you are comparing data obtained from machines operating at different speeds.

## **Output Arguments**

### **Y — Residual signal of the TSA signal**

vector | timetable

Residual signal of the TSA signal, returned as:

- A vector, when the TSA signal is specified as a vector X
- A timetable, when the TSA signal is specified as a timetable XT

The residual signal is computed by removing the components in `orderList` and the shaft signal along with their respective harmonics from X. You can use Y to further extract condition indicators of rotating machinery for predictive maintenance. For example, extracting the root-mean-squared value of the residual signal is useful in identifying changes over time, which indicate potential machine faults. For more information on how Y is computed, see “Algorithms” on page 1-222.

### **S — Amplitude spectrum of the residual signal**

vector

Amplitude spectrum of the residual signal, returned as a vector. S is the normalized fast Fourier transform of the signal Y. S has the same length as the input TSA signal X. For more information on how S is computed, see “Algorithms” on page 1-222.

## Algorithms

### Residual Signal

The residual signal is computed from the TSA signal by removing the following from the signal spectrum:

- Shaft frequency and its harmonics
- Gear meshing frequencies and their harmonics

The frequencies are removed by computing the discrete Fourier transform (DFT) and setting the spectrum values to zero at the specified frequencies. `tsaresidual` uses a bandwidth equal to the shaft speed around the frequencies of interest to filter out the undesired frequency components, as mentioned in [4].

### Amplitude Spectrum

The amplitude spectrum of the residual signal is computed as follows,

$$S = \frac{fft(Y)}{length(Y) * 2}$$

Here, Y is the residual signal.

## References

- [1] McFadden, P.D. "Examination of a Technique for the Early Detection of Failure in Gears by Signal Processing of the Time Domain Average of the Meshing Vibration." *Aero Propulsion Technical Memorandum 434*. Melbourne, Australia: Aeronautical Research Laboratories, Apr. 1986.
- [2] Večeř, P., Marcel Kreidl, and R. Šmíd. "Condition Indicators for Gearbox Monitoring Systems." *Acta Polytechnica* 45.6 (2005), pages 35-43.
- [3] Zakrajsek, J. J., Townsend, D. P., and Decker, H. J. "An Analysis of Gear Fault Detection Methods as Applied to Pitting Fatigue Failure Data." *Technical Memorandum 105950*. NASA, Apr. 1993.
- [4] Zakrajsek, James J. "An investigation of gear mesh failure prediction techniques." National Aeronautics and Space Administration Cleveland OH Lewis Research Center, 1989. No. NASA-E-5049.

## **See Also**

`tsadifference` | `tsaregular`

**Introduced in R2018b**

## update

Update posterior parameter distribution of degradation remaining useful life model

## Syntax

```
update mdl, data
```

## Description

`update(mdl, data)` updates the posterior estimate of the parameters of the degradation remaining useful life (RUL) model `mdl` using the latest degradation measurements in `data`.

## Examples

### Update Exponential Degradation Model in Real Time

Load training data, which is a degradation feature profile for a component.

```
load('expRealTime.mat')
```

For this example, assume that the training data is not historical data. When there is no historical data, you can update your degradation model in real time using observed data.

Create an exponential degradation model with the following settings:

- Arbitrary  $\theta$  and  $\beta$  prior distributions with large variances so that the model relies mostly on observed data
- Noise variance of 0.003

```
mdl = exponentialDegradationModel('Theta',1,'ThetaVariance',1e6,...  
    'Beta',1,'BetaVariance',1e6,...  
    'NoiseVariance',0.003);
```

Since there is no life time variable in the training data, create an arbitrary life time vector for fitting.

```
lifeTime = [1:length(expRealTime)];
```

Observe the degradation feature for 10 iterations. Update the degradation model after each iteration.

```
for i=1:10
    update mdl, [lifeTime(i) expRealTime(i)]
end
```

After observing the model for some time, for example at a steady-state operating point, you can restart the model and save the current posterior distribution as a prior distribution.

```
restart(mdl, true)
```

View the updated prior distribution parameters.

```
mdl.Prior
ans = struct with fields:
    Theta: 2.3555
    ThetaVariance: 0.0058
    Beta: 0.0722
    BetaVariance: 3.6362e-05
    Rho: -0.8429
```

## Input Arguments

### **mdl** — Degradation RUL model

linearDegradationModel object | exponentialDegradationModel object

Degradation RUL model, specified as a `linearDegradationModel` object or an `exponentialDegradationModel` object. `update` updates the posterior estimates of the degradation model parameters based on the latest degradation feature measurements in data.

For a `linearDegradationModel`, the updated parameters are `Theta` and `ThetaVariance`.

For an `exponentialDegradationModel`, the updated parameters are `Theta`, `ThetaVariance`, `Beta`, `BetaVariance`, and `Rho`.

`update` also sets the following properties of `mdl`:

- `InitialLifeTimeValue` — The first time you call `update`, this property is set to the life time value in the first row of `data`.
- `CurrentLifeTimeValue` — Each time you call `update`, this property is set to the life time value in the last row of `data`.
- `CurrentMeasurement` — Each time you call `update`, this property is set to the feature measurement value in the last row of `data`.

### **data — Degradation feature measurements**

two-column array | table object

Degradation feature measurements, specified as one of the following:

- Two-column array — The first column contains life time values and the second column contains the corresponding degradation feature measurement.
- `table` or `timetable` object that contains variables with names that match the `LifeTimeVariable` and `DataVariables` properties of `mdl`.

## See Also

### **Functions**

`exponentialDegradationModel` | `fit` | `linearDegradationModel` | `predictRUL`

### **Topics**

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**

# writeToLastMemberRead

Write data to member of an ensemble datastore

## Syntax

```
writeToLastMemberRead(ensemble, Name, Value)  
writeToLastMemberRead(ensemble, data)
```

## Description

`writeToLastMemberRead(ensemble, Name, Value)` writes the data specified one or more `Name, Value` pair arguments to the last-read member of an ensemble datastore. The last-read member is the member most recently accessed using the `read` command. (See “Data Ensembles for Condition Monitoring and Predictive Maintenance”.) Each `Name` must match an entry in the property `ensemble.DataVariables`. The function writes the corresponding `Value` to the ensemble datastore.

- If `ensemble` is a `simulationEnsembleDatastore` object, then `writeToLastMemberRead` writes the data to the MAT-file corresponding to the last-read ensemble member (`ensemble.LastMemberRead`).
- If `ensemble` is a `fileEnsembleDatastore` object, then `writeToLastMemberRead` uses the function identified by the property `ensemble.WriteToMemberFcn` to write the data. If that property is not defined, then `writeToLastMemberRead` generates an error.

This syntax is not available when the `ReadSize` property of `ensemble` is greater than 1. Use `writeToLastMemberRead(ensemble, data)` instead.

`writeToLastMemberRead(ensemble, data)` writes the data in a table to the last-read ensemble member. The table variables must match entries in the property `ensemble.DataVariables`.

## Examples

## Append Derived Data to Ensemble Members

You can process data in an ensemble datastore and add derived variables to the ensemble members. For this example, process a variable value to compute a label that indicates whether the ensemble member contains data obtained with a fault present. You then add that label to the ensemble.

For this example, use the following code to create a `simulationEnsembleDatastore` object using data previously generated by running a Simulink® model at a various fault values. (See `generateSimulationEnsemble`.) The ensemble includes simulation data for five different values of a model parameter, `ToothFaultGain`. The model was configured to log the simulation data to a variable named `logsout` in the MAT-files that are stored for this example in `simEnsData.zip`. Because of the volume of data, the unzip operation might take a minute or two.

```
unzip simEnsData.zip % extract compressed files
ensemble = simulationEnsembleDatastore(pwd,'logsout')
```

```
ensemble =
  simulationEnsembleDatastore with properties:

    DataVariables: [5x1 string]
  IndependentVariables: [0x0 string]
    ConditionVariables: [0x0 string]
    SelectedVariables: [5x1 string]
        ReadSize: 1
        NumMembers: 5
    LastMemberRead: [0x0 string]
        Files: [5x1 string]
```

Read the data from the first member in the ensemble. The software determines which ensemble is the first member, and updates the property `ensemble.LastMemberRead` to reflect the name of the corresponding file.

```
data = read(ensemble)
```

```
data=1x5 table
  PMSignalLogName      SimulationInput      SimulationMetadata
  _____          _____          _____
  'logsout'           [1x1 Simulink.SimulationInput]  [1x1 Simulink.SimulationMetada
```



By default, all the variables stored in the ensemble data are designated as `SelectedVariables`. Therefore, the returned table row includes all ensemble variables, including a variable `SimulationInput`, which contains the `Simulink.SimulationInput` object that configured the simulation for this ensemble member. That object includes the `ToothFaultGain` value used for the ensemble member, stored in a data structure in its `Variables` property. Examine that value. (For more information about how the simulation configuration is stored, see `Simulink.SimulationInput`.)

```
data.SimulationInput{1}
```

```
ans =
```

```
SimulationInput with properties:
```

```

    ModelName: 'TransmissionCasingSimplified'
  InitialState: [0x0 Simulink.SimState.ModelSimState]
  ExternalInput: []
 ModelParameters: [0x0 Simulink.Simulation.ModelParameter]
BlockParameters: [0x0 Simulink.Simulation.BlockParameter]
    Variables: [1x1 Simulink.Simulation.Variable]
   PreSimFcn: []
   PostSimFcn: []
   UserString: ''

```

```
Inputvars = data.SimulationInput{1}.Variables;
Inputvars.Name
```

```
ans =
```

```
'ToothFaultGain'
```

```
Inputvars.Value
```

```
ans = -2
```

Suppose that you want to convert the `ToothFaultGain` values for each ensemble member into a binary indicator of whether or not a tooth fault is present. Suppose further that you know from your experience with the system that tooth-fault gain values less than 0.1 in magnitude are small enough to be considered healthy operation. Convert the gain value for this ensemble into an indicator that is 0 (no fault) for  $-0.1 < \text{gain} < 0.1$ , and 1 (fault) otherwise.

```
st = abs(Inputvars.Value) < 0.1;
```

To append the new tooth-fault indicator to the corresponding ensemble data, first expand the list of data variables in the ensemble to include a variable for the indicator.

```
ensemble.DataVariables = [ensemble.DataVariables; "ToothFault"];  
ensemble.DataVariables
```

```
ans = 6x1 string array  
    "PMSignalLogName"  
    "SimulationInput"  
    "SimulationMetadata"  
    "Tacho"  
    "Vibration"  
    "ToothFault"
```

This operation is conceptually equivalent to adding a column to the table of ensemble data. Now that `DataVariables` contains the new variable name, assign the derived value to that column of the member using `writeToLastMemberRead`.

```
writeToLastMemberRead(ensemble, 'ToothFault', sT);
```

In practice, you want to append the tooth-fault indicator to every member in the ensemble. To do so, reset the ensemble datastore to its unread state, so that the next read operation starts at the first ensemble member. Then, loop through all the ensemble members, computing `ToothFault` for each member and appending it. The reset operation does not change `ensemble.DataVariables`, so "ToothFault" is still present in that list.

```
reset(ensemble);
```

```
sT = false;  
while hasdata(ensemble)  
    data = read(ensemble);  
    InputVars = data.SimulationInput{1}.Variables;  
    TFGain = InputVars.Value;  
    sT = abs(TFGain) < 0.1;  
    writeToLastMemberRead(ensemble, 'ToothFault', sT);  
end
```

Finally, designate the new tooth-fault indicator as a condition variable in the ensemble datastore. You can use this designation to track and refer to variables in the ensemble data that represent conditions under which the member data was generated.

```
ensemble.ConditionVariables = {"ToothFault"};  
ensemble.ConditionVariables
```

```
ans =
'ToothFault'
```

You can add the new variable to `ensemble.SelectedVariables` when you want to read it out for further analysis. For an example that shows more ways to manipulate and analyze data stored in a `simulationEnsembleDatastore` object, see “Using Simulink to Generate Fault Data”.

## Read from and Write to a File Ensemble Datastore

Create a file ensemble datastore for data stored in MATLAB files, and configure it with functions that tell the software how to read from and write to the datastore. (For more details about configuring file ensemble datastores, see “File Ensemble Datastore With Measured Data”.) Because of the volume of data, the unzip operation takes a few minutes.

```
% Create ensemble datastore that points to datafiles in current folder
unzip fileEnsData.zip % extract compressed files
location = pwd;
extension = '.mat';
fensemble = fileEnsembleDatastore(location,extension);
```

```
% Specify data and condition variables
fensemble.DataVariables = ["gs";"sr";"load";"rate"];
fensemble.ConditionVariables = "label";
```

```
% Configure with functions for reading and writing variable data
addpath(fullfile(matlabroot,'examples','predmaint','main')) % Make sure functions are c
fensemble.ReadFcn = @readBearingData;
fensemble.WriteToMemberFcn = @writeBearingData;
```

The functions tell the `read` and `writeToLastMemberRead` commands how to interact with the data files that make up the ensemble. Thus, when you call the `read` command, it uses `readBearingData` to read all the variables in `fensemble.SelectedVariables`. For this example, `readBearingData` extracts requested variables from a structure, `bearing`, and other variables stored in the file. It also parses the filename for the fault status of the data.

Specify variables to read, and read them from the first member of the ensemble.

```
fensemble.SelectedVariables = ["gs";"load";"label"];  
data = read(fensemble)
```

```
data=1x3 table  
      label          gs          load  
      _____  _____  _____  
      "Faulty"    [146484x1 double]    0
```

You can now process the data from the member as needed. For this example, compute the average value of the signal stored in the variable `gs`. Extract the data from the table returned by `read`.

```
gsdata = data.gs{1};  
gsmean = mean(gsdata);
```

You can write the mean value `gsmean` back to the data file as a new variable. To do so, first expand the list of data variables in the ensemble to include a variable for the new value. Call the new variable `gsMean`.

```
fensemble.DataVariables = [fensemble.DataVariables;"gsMean"]
```

```
fensemble =  
  fileEnsembleDatastore with properties:  
  
          ReadFcn: @readBearingData  
    WriteToMemberFcn: @writeBearingData  
      DataVariables: [5x1 string]  
IndependentVariables: [0x0 string]  
ConditionVariables: "label"  
SelectedVariables: [3x1 string]  
      ReadSize: 1  
      NumMembers: 5  
LastMemberRead: "C:\TEMP\Bdoc18b_943130_7372\ib632619\14\tpf2dcb597\predmainn  
      Files: [5x1 string]
```

Next, write the derived mean value to the file corresponding to the last-read ensemble member. (See “Data Ensembles for Condition Monitoring and Predictive Maintenance”.) When you call `writeToLastMemberRead`, it converts the data to a structure and calls `fensemble.WriteToMemberFcn` to write the data to the file.

```
writeToLastMemberRead(fensemble, 'gsMean',gsmean);
```

Calling `read` again advances the last-read-member indicator to the next file in the ensemble and reads the data from that file.

```
data = read(fensemble)
```

```
data=1x3 table
      label          gs          load
      -----
      "Faulty"      [146484x1 double]    50
```

You can confirm that this data is from a different member by examining the `load` variable in the table. Here, its value is 50, while in the previously read member, it was 0.

You can repeat the processing steps to compute and append the mean for this ensemble member. In practice, it is more useful to automate the process of reading, processing, and writing data. To do so, reset the ensemble to a state in which no data has been read. Then loop through the ensemble and perform the read, process, and write steps for each member.

```
reset(fensemble)
while hasdata(fensemble)
    data = read(fensemble);
    gsdata = data.gs{1};
    gsmean = mean(gsdata);
    writeToLastMemberRead(fensemble, 'gsMean', gsmean);
end
```

The `hasdata` command returns `false` when every member of the ensemble has been read. Now, each data file in the ensemble includes the `gsMean` variable derived from the data `gs` in that file. You can use techniques like this loop to extract and process data from your ensemble files as you develop a predictive-maintenance algorithm. For an example illustrating in more detail the use of a file ensemble datastore in the algorithm-development process, see “Rolling Element Bearing Fault Diagnosis”. The example also shows how to use Parallel Computing Toolbox™ to speed up the processing of large data ensembles.

To confirm that the derived variable is present in the file ensemble datastore, read it from the first and second ensemble members. To do so, reset the ensemble again, and add the new variable to the selected variables. In practice, after you have computed derived values, it can be useful to read only those values without rereading the unprocessed data, which can take significant space in memory. For this example, read selected variables that include the new variable, `gsMean`, but do not include the unprocessed data, `gs`.

```
reset(fensemble)
fensemble.SelectedVariables = ["label";"load";"gsMean"];
data1 = read(fensemble)
```

```
data1=1×3 table
    label    load    gsMean
    _____  _____  _____
    "Faulty"    0    -0.23
```

```
data2 = read(fensemble)
```

```
data2=1×3 table
    label    load    gsMean
    _____  _____  _____
    "Faulty"    50    -0.22352
```

```
rmpath(fullfile(matlabroot,'examples','predmaint','main')) % Reset path
```

## Input Arguments

### **ensemble** — Ensemble datastore

simulationEnsembleDatastore object | fileEnsembleDatastore object

Ensemble datastore to add data variables to, specified as a:

- simulationEnsembleDatastore object
- fileEnsembleDatastore object

`writeToLastMemberRead` writes the data to the last-read member of the specified ensemble, identified by the `LastMemberRead` property of the ensemble. The last-read ensemble member is the member most recently accessed using the `read` command. (See “Data Ensembles for Condition Monitoring and Predictive Maintenance”.)

### **data** — New data

table

New data to write to the current ensemble member, specified as a `table`. For example, suppose that you have calculated two values that you want to add to the current member:

a vector stored as the MATLAB workspace variable `Afilt`, and a scalar stored as `Amean`. Use the following command to construct data.

```
data = table(Afilt,Amean,'VariableNames',{'Afilt','Amean'});
```

The number of rows in the table must match the `ReadSize` property of `ensemble`. By default, `ReadSize = 1`, and you write a single table row to a single ensemble member. When you configure `ensemble` to read multiple members at once, you must write to the same number of members. For instance, if `ReadSize = 3`, then `data` is a three-row table.

## Limitations

- When you use a `simulationEnsembleDatastore` to manage data at a remote location, such as cloud storage using Amazon S3™ (Simple Storage Service), Windows Azure® Blob Storage, and Hadoop® Distributed File System (HDFS™), you cannot use `writeToLastMemberRead` to add data to the ensemble datastore.

## See Also

`fileEnsembleDatastore` | `read` | `simulationEnsembleDatastore`

## Topics

“Data Ensembles for Condition Monitoring and Predictive Maintenance”

**Introduced in R2018a**





# Objects – Alphabetical List

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# covariateSurvivalModel

Proportional hazard survival model for estimating remaining useful life

## Description

Use `covariateSurvivalModel` to estimate the remaining useful life (RUL) of a component using a proportional hazard survival model. This model describes the survival probability of a test component using historical information about the life span of components and associated covariates. Covariates are environmental or explanatory variables, such as the component manufacturer or operating conditions. Covariate survival models are useful when the only data you have is the failure times and associated covariates for an ensemble of similar components, such as multiple machines manufactured to the same specifications. For more information on the survival model, see “Proportional Hazard Survival Model” on page 2-11.

To configure a `covariateSurvivalModel` object for a specific type of component, use `fit`, which estimates model coefficients using a collection of failure-time data and associated covariates. After you configure the parameters of your covariate survival model, you can then predict the remaining useful life of similar components using `predictRUL`. For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

If you have only life span measurements and do not have covariate information, use a `reliabilitySurvivalModel`.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

## Creation

## Syntax

```
mdl = covariateSurvivalModel  
mdl = covariateSurvivalModel(initModel)
```

```
mdl = covariateSurvivalModel( ____, Name, Value)
```

## Description

`mdl = covariateSurvivalModel` creates a covariate survival model for estimating RUL and initializes the model with default settings.

`mdl = covariateSurvivalModel(initModel)` creates a covariate survival model and initializes the model parameters using an existing `covariateSurvivalModel` object `initModel`.

`mdl = covariateSurvivalModel( ____, Name, Value)` specifies user-settable model properties using name-value pairs. For example, `covariateSurvivalModel('LifeTimeUnit', "days")` creates a covariate survival model with that uses days as a lifetime unit. You can specify multiple name-value pairs. Enclose each property name in quotes.

## Input Arguments

### **initModel** — Covariate survival model

`covariateSurvivalModel` object

Covariate survival model, specified as a `covariateSurvivalModel` object.

## Properties

### **BaselineCumulativeHazard** — Baseline hazard rate function

two-column array

This property is read-only.

Baseline hazard rate of the survival model, specified as a two-column array and estimated by the `fit` function. The second column contains the baseline survivor functions values, and the first column contains the corresponding lifetime values.

For more information on the survival model, see “Proportional Hazard Survival Model” on page 2-11.

### **EncodingMethod** — Encoding method

"dummy" (default) | "binary"

Encoding method for the categorical features in `EncodedVariables`, specified as one of the following:

- "dummy" — For a categorical feature with  $N$  categories, encode the variable using  $(N - 1)$  bits.
- "binary" — Binary encoding

You can specify `EncodingMethod`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Standardize — Flag for standardizing covariate features**

`false` (default) | `true`

Flag for standardizing covariate features when calculating Cox regression parameters, specified as a logical value. When `Standardize` is `true`, numeric covariate variables are standardized such that covariate  $X$  becomes  $(X - \text{mean}(X)) / \text{std}(X)$ .

Standardization does not affect encoded categorical variables.

You can specify `Standardize`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Ties — Method for handling tied failure times**

"breslow" (default) | "efron"

Method for handling tied failure times, specified as either "breslow" or "efron". For more information on these methods, see "Cox Proportional Hazards Model" (Statistics and Machine Learning Toolbox).

You can specify `Ties`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Options — Numerical and display settings**

structure

Numerical and display settings for Cox regression, specified as a structure created using `statset('coxphfit')`. You can modify the options in the structure using dot notation.

You can specify Options:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **ParameterValues — Covariate multiplying coefficients**

vector

This property is read-only.

Covariate multiplying coefficients of the survival model, specified as a scalar and estimated by the `fit` function. For more information on the survival model, see “Proportional Hazard Survival Model” on page 2-11.

### **ParameterCovariance — Covariance of covariate multiplying coefficients**

array

This property is read-only.

Covariance of the covariate multiplying coefficients, specified as a positive array with size equal to the number of coefficients and estimated by the `fit` function.

### **ParameterNames — Covariate multiplying coefficient names**

string array

This property is read-only.

Covariate multiplying coefficient names specified as a string array and assigned when the model is trained using the `fit` function.

Coefficients corresponding to numeric covariates have the same name as the corresponding data variable in `DataVariables`. For encoded variables, the coefficient names contain the name of the corresponding encoded variable from `EncodedVariables` and a representation of the encoded bit order.

### **CensorVariable — Censor variable**

"" (default) | string

Censor variable, specified as a string that contains a valid MATLAB variable name. The censor variable is a binary variable that indicates which life-time measurements in `data` are not end-of-life values.

`CensorVariable` must not match any of the strings in `DataVariables` or `LifeTimeVariable`.

You can specify `CensorVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **LifeTimeVariable — Lifetime variable**

"" (default) | string

Lifetime variable, specified as a string that contains a valid MATLAB variable name. For survival models, the lifetime variable contains the historical life span measurements of components.

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Manually using dot notation

### **LifeTimeUnit — Lifetime variable units**

"" (default) | string

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).

### **DataVariables — Covariate data variable**

"" (default) | string | string array

Covariate data variables, specified as a string or string array. The strings in `DataVariables` must be valid MATLAB variable names. Covariates are also called environmental or explanatory variables.

You can specify `DataVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **EncodedVariables — Encoded covariate variables**

"" (default) | string | string array

Encoded covariate variables, specified as a string or string array. The strings in `EncodedVariables` must be valid MATLAB variable names. Encoded variables are usually nonnumeric categorical features that `fit` converts to numeric vectors before fitting. You can also designate logical or numeric values that take values from a small set to be encoded.

To specify the method of encoding, use `EncodingMethod`.

You can specify `EncodedVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

The strings in `EncodedVariables` must be a subset of the strings in `DataVariables`.

### **UserData — Additional model information**

[] (default) | any data type or format

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify `UserData`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

## **Object Functions**

<code>predictRUL</code>	Estimate remaining useful life for a test component
<code>fit</code>	Estimate parameters of remaining useful life model using historical data

`plot` Plot survivor function for covariate survival remaining useful life model

## Examples

### Train Covariate Survival Model

Load training data.

```
load('covariateData.mat')
```

This data contains battery discharge times and related covariate information. The covariate variables are:

- Temperature
- Load
- Manufacturer

The manufacturer information is a categorical variable that must be encoded.

Create a covariate survival model.

```
mdl = covariateSurvivalModel;
```

Train the survival model using the training data, specifying the life time variable, data variables, and encoded variable. There is no censor variable for this training data.

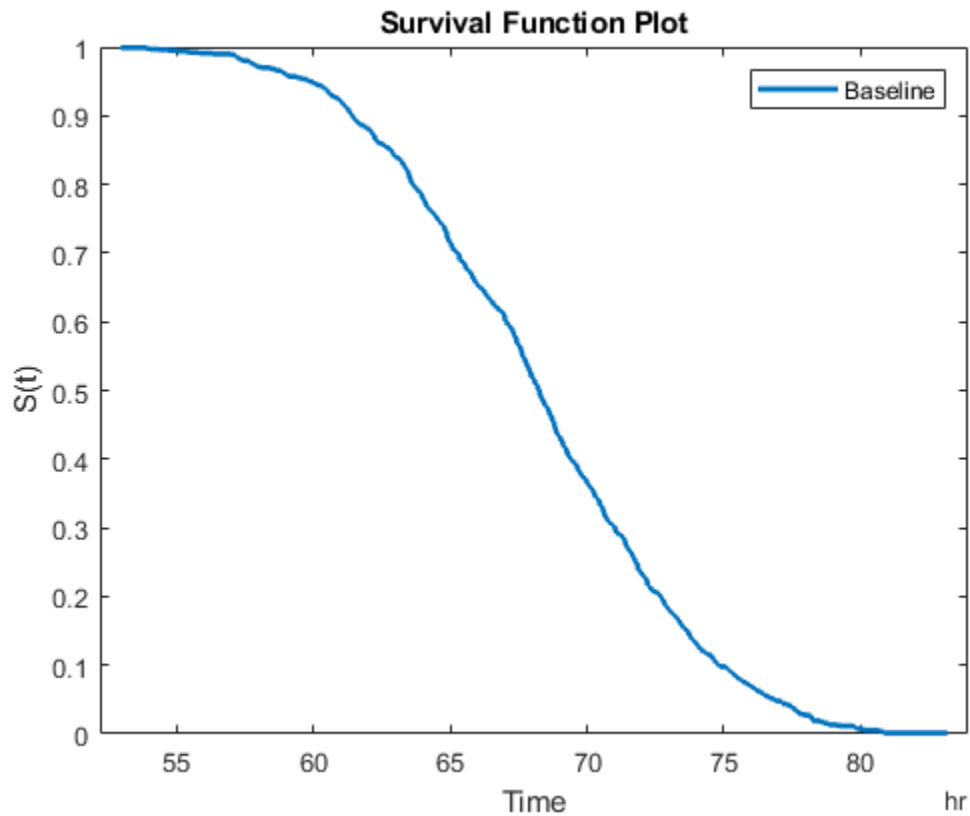
```
fit(mdl,covariateData,"DischargeTime",["Temperature","Load","Manufacturer"],[],"Manufa
```

```
Successful convergence: Norm of gradient less than OPTIONS.TolFun
```

Plot the baseline survivor function for the model.

```
plot(mdl)
```





### Predict RUL Using Covariate Survival Model

Load training data.

```
load('covariateData.mat')
```

This data contains battery discharge times and related covariate information. The covariate variables are:

- Temperature

- Load
- Manufacturer

The manufacturer information is a categorical variable that must be encoded.

Create a covariate survival model, and train it using the training data.

```
mdl = covariateSurvivalModel('LifeTimeVariable',"DischargeTime",'LifeTimeUnit',"hours",  
    'DataVariables',["Temperature","Load","Manufacturer"],'EncodedVariables',"Manufacturer"  
fit(mdl,covariateData)
```

```
Successful convergence: Norm of gradient less than OPTIONS.TolFun
```

Suppose you have a battery pack manufactured by maker B that has run for 30 hours. Create a test data table that contains the usage time, `DischargeTime`, and the measured ambient temperature, `TestAmbientTemperature`, and current drawn, `TestBatteryLoad`.

```
TestBatteryLoad = 25;  
TestAmbientTemperature = 60;  
DischargeTime = hours(30);  
TestData = timetable(TestBatteryLoad,TestAmbientTemperature,'B','RowTimes',hours(30));  
TestData.Properties.VariableNames = {'Temperature','Load','Manufacturer'};  
TestData.Properties.DimensionNames{1} = 'DischargeTime';
```

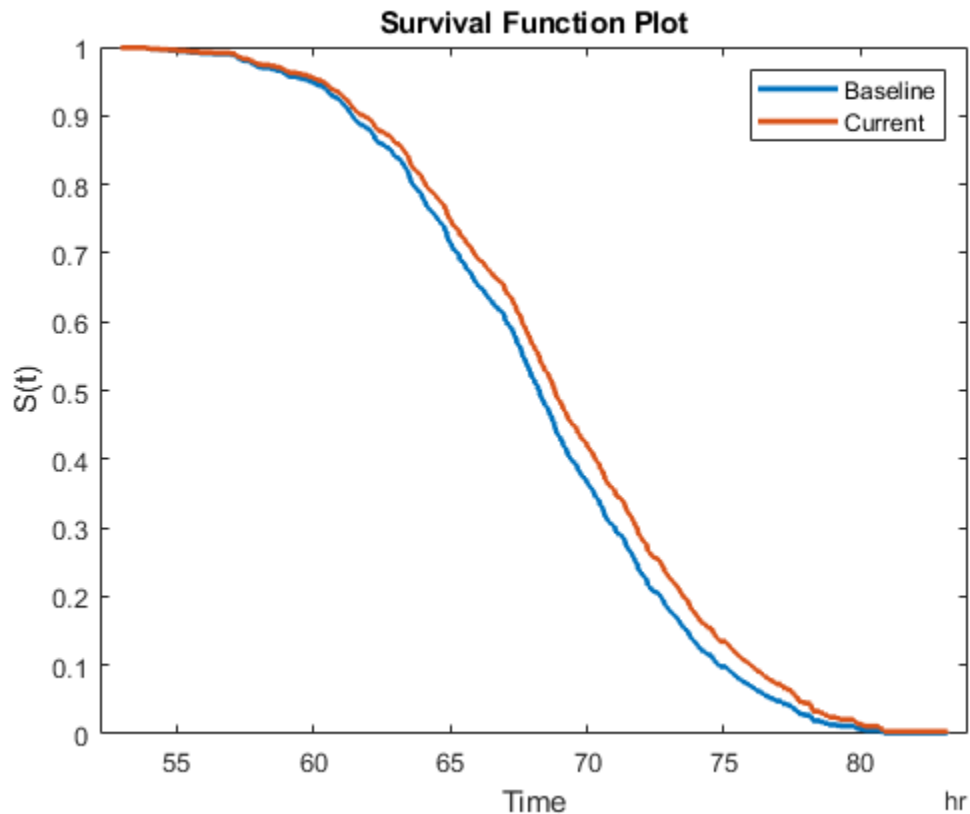
Predict the RUL for the battery.

```
estRUL = predictRUL(mdl,TestData)
```

```
estRUL = duration  
    38.657 hr
```

Plot the survivor function for the covariate data of the battery.

```
plot(mdl,TestData)
```



## Algorithms

### Proportional Hazard Survival Model

The `covariateSurvivalModel` object implements the following proportional hazard survival model:

$$h(X, t) = h_0(t) e^{b^T X}$$

where:

- $X$  is a vector covariate values.
- $b$  is a vector of covariate multiplying coefficients. These coefficients correspond to the `ParameterValues` property of the model.
- $h_0(t)$  is the baseline hazard rate function, which corresponds to the `BaselineCumulativeHazard` property of the model.
- $h(X,t)$  is the hazard rate at time  $t$  for  $X$ .

To find the parameters of this model, the `fit` function uses the `coxphfit` function.

For more information on proportional hazard models, see “Cox Proportional Hazards Model” (Statistics and Machine Learning Toolbox).

## See Also

### Functions

`coxphfit` | `fit` | `predictRUL` | `reliabilitySurvivalModel`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

“Cox Proportional Hazards Model” (Statistics and Machine Learning Toolbox)

### Introduced in R2018a

# exponentialDegradationModel

Exponential degradation model for estimating remaining useful life

## Description

Use `exponentialDegradationModel` to model an exponential degradation process for estimating the remaining useful life (RUL) of a component. Degradation models estimate the RUL by predicting when a monitored signal will cross a predefined threshold. Exponential degradation models are useful when the component experiences cumulative degradation. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

To configure an `exponentialDegradationModel` object for a specific type of component, you can:

- Estimate the model parameters using historical data regarding the health of an ensemble of similar components, such as multiple machines manufactured to the same specifications. To do so, use `fit`.
- Specify the model parameters when you create the model based on your knowledge of the component degradation process.

Once you configure the parameters of your degradation model, you can then predict the remaining useful life of similar components using `predictRUL`. For a basic example illustrating RUL prediction with a degradation model, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

## Creation

## Syntax

```
mdl = exponentialDegradationModel
```

```
mdl = exponentialDegradationModel(Name,Value)
```

### Description

`mdl = exponentialDegradationModel` creates an exponential degradation model for estimating RUL and initializes the model with default settings.

`mdl = exponentialDegradationModel(Name,Value)` specifies user-settable model properties using name-value pairs. For example, `exponentialDegradationModel('NoiseVariance',0.5)` creates an exponential degradation model with a model noise variance of 0.5. You can specify multiple name-value pairs. Enclose each property name in quotes.

### Properties

#### Theta — Current mean value of the $\theta$ parameter

scalar

This property is read-only.

Current mean value of the  $\theta$  parameter in the degradation model, specified as a scalar. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify Theta using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of Theta changes when you use the `update` function.

#### ThetaVariance — Current variance of the $\theta$ parameter

nonnegative scalar

This property is read-only.

Current variance of the  $\theta$  parameter in the degradation model, specified as a nonnegative scalar. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify `ThetaVariance` using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of `ThetaVariance` changes when you use the `update` function.

### **Beta — Current mean value of the $\beta$ parameter**

scalar

This property is read-only.

Current mean value of the  $\beta$  parameter in the degradation model, specified as a scalar. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify `Beta` using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of `Beta` changes when you use the `update` function.

### **BetaVariance — Current variance of the $\beta$ parameter**

nonnegative scalar

This property is read-only.

Current variance of the  $\beta$  parameter in the degradation model, specified as a nonnegative scalar. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify `BetaVariance` using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of `BetaVariance` changes when you use the `update` function.

### **Rho — Current correlation between $\theta$ and $\beta$**

0 (default) | scalar value in the range [-1,1]

This property is read-only.

Current correlation between  $\theta$  and  $\beta$ , specified as a scalar value in the range [-1,1]. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify Rho using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of Rho changes when you use the `update` function.

### **Phi — Current intercept value**

scalar

Current intercept value  $\phi$  in the degradation model, specified as a scalar. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify Phi using a name-value pair argument when you create the model. Otherwise, the value of Phi changes when you estimate the model prior using the `fit` function.

### **Prior — Prior information about model parameters**

structure

Prior information about model parameters, specified as a structure with the following fields:

- `Theta` — Mean value of  $\theta$
- `ThetaVariance` — Variance of  $\theta$
- `Beta` — Mean value of  $\beta$
- `BetaVariance` — Variance of  $\beta$
- `Rho` — Correlation between  $\theta$  and  $\beta$ .

You can specify the fields of `Prior`:

- When you create the model. When you specify `Theta`, `ThetaVariance`, `Beta`, `BetaVariance`, or `Rho` at model creation using name-value pairs, the corresponding field of `Prior` is also set.
- Using the `fit` function. In this case, the prior values are derived from the data used to fit the model.



- Using the `restart` function. In this case, the current values of `Theta`, `ThetaVariance`, `Beta`, `BetaVariance`, and `Rho` are copied to the corresponding fields of `Prior`.
- Using dot notation after model creation.

For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

### **NoiseVariance — Variance of additive noise**

1 (default) | nonnegative scalar

Variance of additive noise  $\varepsilon$  in the degradation model, specified as a nonnegative scalar. For more information on the degradation model, see “Exponential Degradation Model” on page 2-24.

You can specify `NoiseVariance`:

- Using a name-value pair when you create the model
- Using a name-value pair with the `restart` function
- Using dot notation after model creation

### **SlopeDetectionLevel — Slope detection level**

0.05 (default) | scalar value in the range [0,1] | []

Slope detection level for determining the start of the degradation process, specified as a scalar in the range [0,1]. This value corresponds to the alpha value in a t-test of slope significance.

To disable the slope detection test, set `SlopeDetectionLevel` to [].

You can specify `SlopeDetectionLevel`:

- Using a name-value pair when you create the model
- Using a name-value pair with the `restart` function
- Using dot notation after model creation

### **CurrentMeasurement — Latest degradation feature value**

scalar

This property is read-only.

Latest degradation feature value supplied to the update function, specified as a scalar.

### **InitialLifeTimeValue** — Initial lifetime variable value

scalar | duration object

This property is read-only.

Initial lifetime variable value when the update function is first called on the model, specified as a scalar.

When the model detects a slope, the `InitialLifeTime` value is changed to match the `SlopeDetectionInstant` value.

### **CurrentLifeTimeValue** — Current lifetime variable value

scalar | duration object

This property is read-only.

Latest lifetime variable value supplied to the update function, specified as a scalar.

### **LifeTimeVariable** — Lifetime variable

"" (default) | string

Lifetime variable, specified as a string that contains a valid MATLAB variable name or "".

When you train the model using the `fit` function, if your training data is a:

- `table`, then `LifeTimeVariable` must match one of the variable names in the table
- `timetable`, then `LifeTimeVariable` one of the variable names in the table or the dimension name of the time variable, `data.Properties.DimensionNames{1}`

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **LifeTimeUnit** — Lifetime variable units

"" (default) | string

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).

**DataVariables — Degradation variable name**

`""` (default) | string

Degradation variable name, specified as a string that contains a valid MATLAB variable name. Degradation models have only one data variable.

You can specify `DataVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

**UseParallel — Flag for using parallel computing**

`false` (default) | `true`

Flag for using parallel computing when fitting prior values from data, specified as either `true` or `false`.

You can specify `UseParallel`:

- Using a name-value pair when you create the model
- Using a name-value pair with the `restart` function
- Using dot notation after model creation

**UserData — Additional model information**

`[]` (default) | any data type or format

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify `UserData`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### Object Functions

fit	Estimate parameters of remaining useful life model using historical data
predictRUL	Estimate remaining useful life for a test component
update	Update posterior parameter distribution of degradation remaining useful life model
restart	Reset remaining useful life degradation model

### Examples

#### Train Exponential Degradation Model

Load training data.

```
load('expTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create an exponential degradation model with default settings.

```
mdl = exponentialDegradationModel;
```

Train the degradation model using the training data.

```
fit(mdl,expTrainVectors)
```

#### Create Exponential Degradation Model with Known Priors

Create an exponential degradation model, and configure it with a known prior distribution.

```
mdl = exponentialDegradationModel('Theta',0.5,'ThetaVariance',0.003,...  
    'Beta',0.3,'BetaVariance',0.002,...  
    'Rho',0.1);
```

The specified prior distribution parameters are stored in the `Prior` property of the model.

```
mdl.Prior
ans = struct with fields:
    Theta: 0.5000
    ThetaVariance: 0.0030
    Beta: 0.3000
    BetaVariance: 0.0020
    Rho: 0.1000
```

The current posterior distribution of the model is also set to match the specified prior distribution. For example, check the posterior value of the correlation parameter.

```
mdl.Rho
ans = 0.1000
```

## Train Exponential Degradation Model Using Tabular Data

Load training data.

```
load('expTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a exponential degradation model with default settings.

```
mdl = exponentialDegradationModel;
```

Train the degradation model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,expTrainTables,"Time","Condition")
```

## Predict RUL Using Exponential Degradation Model

Load training data.

```
load('expTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Hours" variable and corresponding degradation feature measurements in the "Condition" variable.

Create an exponential degradation model, specifying the life time variable units.

```
mdl = exponentialDegradationModel('LifeTimeUnit','hours');
```

Train the degradation model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,expTrainTables,"Time","Condition")
```

Load testing data, which is a run-to-failure degradation profile for a test component. The test data is a table with the same life time and data variables as the training data.

```
load('expTestData.mat')
```

Based on knowledge of the degradation feature limits, define a threshold condition indicator value that indicates the end-of-life of a component.

```
threshold = 500;
```

Assume that you measure the component condition indicator every hour for 150 hours. Update the trained degradation model with each measurement. Then, predict the remaining useful life of the component at 150 hours. The RUL is the forecasted time at which the degradation feature will pass the specified threshold.

```
for t = 1:150
    update(mdl,expTestData(t,:))
end
estRUL = predictRUL(mdl,threshold)
```

```
estRUL = duration
        136.63 hr
```

The estimated RUL is around 137 hours, which indicates a total predicted life span of 287 hours.

## Update Exponential Degradation Model and Predict RUL

Load observation data.

```
load('expTestData.mat')
```

For this example, assume that the training data is not historical data, but rather real-time observations of the component condition.

Based on knowledge of the degradation feature limits, define a threshold condition indicator value that indicates the end-of-life of a component.

```
threshold = 500;
```

Create an exponential degradation model arbitrary prior distribution data and a specified noise variance. Also, specify the life time and data variable names for the observation data.

```
mdl = exponentialDegradationModel('Theta',1,'ThetaVariance',1e6,...
    'Beta',1,'BetaVariance',1e6,...
    'NoiseVariance',0.003,...
    'LifeTimeVariable',"Time", 'DataVariables',"Condition",
    'LifeTimeUnit',"hours");
```

Observe the component condition for 100 hours, updating the degradation model after each observation.

```
for i=1:100
    update(mdl,expTestData(i,:));
end
```

After 100 hours, predict the RUL of the component using the current life time value stored in the model. Also, obtain the confidence interval associated with the estimated RUL.

```
estRUL = predictRUL(mdl,threshold)
```

```
estRUL = duration
    234.56 hr
```

The estimated RUL is about 234 hours, which indicates a total predicted life span of 334 hours.

## Algorithms

### Exponential Degradation Model

The `exponentialDegradationModel` object implements the following continuous-time exponential degradation model:

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

where:

- $\phi$  is the model intercept, which is constant. You can initialize  $\phi$  as the lower or upper bound on the feasible region of the degradation variable using `Phi`. If the sign of  $\theta$  is:
  - Positive, then  $\phi$  is a lower bound.
  - Negative, then  $\phi$  is an upper bound.
- $\theta(t)$  is a random variable modeled as a lognormal distribution with mean `Theta` and variance `ThetaVariance`.
- $\beta(t)$  is a random variable modeled as a Gaussian distribution with mean `Beta` and variance `BetaVariance`.
- $\varepsilon(t)$  is the model additive noise and is modeled as a normal distribution with zero mean and variance `NoiseVariance`.
- $\sigma$  is equal to `NoiseVariance`.

## Extended Capabilities

### Automatic Parallel Support

Accelerate code by automatically running computation in parallel using `Parallel Computing Toolbox™`.

To evaluate these models in parallel, set the `UseParallel` property to `true`.



## See Also

### Functions

`fit` | `linearDegradationModel` | `predictRUL` | `update`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**

# fileEnsembleDatastore

Manage ensemble data in custom file format

## Description

A `fileEnsembleDatastore` object is a datastore specialized for use in developing algorithms for condition monitoring and predictive maintenance using measured data.

An ensemble is a collection of member data stored in a collection of files. The `fileEnsembleDatastore` object specifies the data variables, independent variables, and condition variables in the ensemble. You provide functions that tell the `fileEnsembleDatastore` object how to read each type of variable from the collection of files. Therefore, you can use `fileEnsembleDatastore` to manage ensemble data stored in any file format or configuration of variables.

The data for a `fileEnsembleDatastore` object can be stored at any location supported by MATLAB datastores, including remote locations, such as cloud storage using Amazon S3 (Simple Storage Service), Windows Azure Blob Storage, and Hadoop Distributed File System (HDFS).

For a detailed example illustrating the use of a file ensemble datastore, see “File Ensemble Datastore With Measured Data”. For general information about data ensembles in Predictive Maintenance Toolbox, see “Data Ensembles for Condition Monitoring and Predictive Maintenance”.

## Creation

## Syntax

```
fensemble = fileEnsembleDatastore(location,extension)  
fensemble = fileEnsembleDatastore(location,extension,Name,Value)
```

## Description

`fensemble = fileEnsembleDatastore(location, extension)` creates a `fileEnsembleDatastore` object that points to data at the file path specified by `location` and having the specified file extension. Set properties of the object to specify the functions for reading from and writing to the ensemble datastore.

`fensemble = fileEnsembleDatastore(location, extension, Name, Value)` specifies additional properties on page 2-27 of the object using one or more name-value pair arguments. For example, using `'ConditionVariables', ["FaultCond"; "ID"]` specifies the condition variables when you create the object.

## Input Arguments

### location — File path

string | character vector

File path from which to read ensemble data, specified as a string or a character vector, and specifying the directory where all the data is stored. The file path can be any location supported by MATLAB datastores, including an IRI path pointing to a remote location, such as cloud storage using Amazon S3 (Simple Storage Service), Windows Azure Blob Storage, and Hadoop Distributed File System (HDFS). For more information about working with remote data in MATLAB, see “Work with Remote Data” (MATLAB).

Example: `pwd + "\simResults"`

### extension — File extension

string | character vector | string vector

File extension for files in the datastore, specified as a string or a character vector, such as `".mat"` or `'.csv'`.

If the datastore contains files having more than one extension, specify them as a string vector, such as `[".xls", ".xlsx"]`. The functions that you supply for the `ReadFcn` and `WriteToMemberFcn` properties must be able to interact with all specified file types.

## Properties

### ReadFcn — Function for reading all selected variables

`[]` (default) | function handle

Function for reading all selected variables from the ensemble, specified as a handle to a function you provide. You write a function that instructs the software how to read variables from a data file containing a member of your ensemble. The function has:

- Two inputs, a file name (string), and the names of signals (string vector) to load from the file
- One output, a table row with table variables for each independent variable

When you specify `ReadFcn`, the software uses this function to read all selected variables from the ensemble, regardless of whether they are named in `DataVariables`, `IndependentVariables`, or `ConditionVariables`.

For example, suppose that you write the following function, `readVars`, for reading variables from your files. This function creates a table containing the variables in a data file that match those in the input string vector, `variables`.

```
function data = readVars(filename,variables)
data = table();
mfile = matfile(filename); % Allows partial loading
for ct=1:numel(variables)
    val = mfile.(variables{ct});
    if numel(val) > 1
        val = {val};
    end
    data.(variables{ct}) = val;
end
end
```

Save the function in a MATLAB file in the current folder or on the path. Then, if you create a `fileEnsembleDatastore` called `fensemble`, set `ReadFcn` as follows.

```
fensemble.ReadFcn = @readVars;
```

When you call `read(fensemble)`, the software uses `readVars` to read all the variables in the `SelectedVariables` property of the ensemble datastore. You must set this property to read data from a `fileEnsembleDatastore` member. Otherwise, `read` generates an error.

### **writeToMemberFcn — Function for adding data**

[ ] (default) | function handle

Function for writing data to the last-read member of the ensemble, specified as a handle to a function you provide. You write a function that instructs the software how to write variables to a data file containing a member of your ensemble. The function has:

- Two inputs, a file name (string), and a data structure whose field names are the data variables to write, and whose values are the corresponding values
- No outputs

For example, suppose that you write the following function, `writeNewData`, for writing data to your files. This function writes an input data structure to the specified data file.

```
function writeNewData(filename,data)
save(filename, '-append', '-struct', 'structData');
end
```

Store `writeNewData` in a MATLAB file in the current folder or on the path. Then, if you create a `fileEnsembleDatastore` called `fensemble`, set `writeToMemberFcn` as follows:

```
fensemble.writeToMemberFcn = @writeNewData;
```

When you call the `writeToLastMemberRead` command on `fensemble`, the software uses `writeNewData` to add the new data to the data file of the last-read ensemble member. You must set this property to add data to a `fileEnsembleDatastore` member. Otherwise, `writeToLastMemberRead` generates an error.

### **DataVariables — Data variables in the ensemble**

[ ] (default) | string array

Data variables in the ensemble, specified as a string array. Data variables are the main content of the members of an ensemble. Data variables can include measured data or derived data for analysis and development of predictive maintenance algorithms. For example, your data variables might include measured or simulated vibration signals and derived values such as mean vibration value or peak vibration frequency. In practice, your data variables, independent variables, and condition variables are all distinct sets of variables.

You can also specify `DataVariables` using a cell array of character vectors, such as `{'Vibration'; 'Tacho'}`, but the variable names are always stored as a string array, `["Vibration"; "Tacho"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **IndependentVariables — Independent variables in the ensemble**

[ ] (default) | string array

Independent variables in the ensemble, specified as a string array. You typically use independent variables to order the members of an ensemble. Examples are timestamps, number of operating hours, or miles driven. Set this property to the names of such variables in your ensemble. In practice, your data variables, independent variables, and condition variables are all distinct sets of variables.

You can also specify `IndependentVariables` using a cell array of character vectors, such as `{'Time'; 'Age'}`, but the variable names are always stored as a string array, `["Time"; "Age"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **ConditionVariables — Condition variables in the ensemble**

[ ] (default) | string array

Condition variables in the ensemble, specified as a string array. Use condition variables to label the members in a ensemble according to the fault condition or other operating condition under which the ensemble member was collected. In practice, your data variables, independent variables, and condition variables are all distinct sets of variables.

You can also specify `ConditionVariables` using a cell array of character vectors, such as `{'GearFault'; 'Temperature'}`, but the variable names are always stored as a string array, `["GearFault"; "Temperature"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **SelectedVariables — Variables to read**

[ ] (default) | string array

Variables to read from the ensemble, specified as a string array. Use this property to specify which variables are extracted to the MATLAB workspace when you use the `read` command to read data from the current member ensemble. `read` returns a table row containing a table variable for each name specified in `SelectedVariables`. For example, suppose that you have an ensemble, `fensemble`, that contains six variables, and you want to read only two of them, `Vibration` and `FaultState`. Set the `SelectedVariables` property and call `read`:

```
fensemble.SelectedVariables = ["Vibration"; "FaultState"];  
data = read(fensemble)
```

`SelectedVariables` can be any combination of the variables in the `DataVariables`, `ConditionVariables`, and `IndependentVariables` properties. If `SelectedVariables` is empty, `read` generates an error.

You can specify `SelectedVariables` using a cell array of character vectors, such as `{'Vibration'; 'Tacho'}`, but the variable names are always stored as a string array, `["Vibration"; "Tacho"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **ReadSize — Number of members to read**

1 (default) | positive integer

Number of members to read from the ensemble datastore at once, specified as a positive integer that is smaller than the total number of members in the ensemble. By default, the `read` command returns a one-row table containing data from one ensemble member. To read data from multiple members in a single `read` operation, set this property to an integer value greater than one. For example, if `ReadSize = 3`, then `read` returns a three-row table where each row contains data from a different ensemble member. If fewer than `ReadSize` members are unread, then `read` returns a table with as many rows as there are remaining members.

The ensemble datastore property `LastMemberRead` contains the names of all files read during the most recent `read` operation. Thus, for instance, if `ReadSize = 3`, then a `read` operation sets `LastMemberRead` to a string vector containing three file names.

When you use `writeToLastMemberRead`, specify the data to write as a table with a number of rows equal to `ReadSize`. The `writeToLastMemberRead` command updates the members specified by `LastMemberRead`, writing one table row to each specified file.

Changing the `ReadSize` property also resets the ensemble to its unread state. For instance, suppose that you read some ensemble members one at a time (`ReadSize = 1`), and then change `ReadSize` to 3. The next `read` operation returns data from the first three ensemble members.

### **NumMembers — Number of members in ensemble**

positive integer

This property is read-only.

Number of members in the ensemble, specified as a positive integer.

### **LastMemberRead — File name of last ensemble member read**

"" (default) | string | string array

This property is read-only.

File name of last ensemble member read into the MATLAB workspace, specified as a string. When you use the `read` command to read data from an ensemble datastore, the software determines which ensemble member to read next, and reads data from the corresponding file. The `LastMemberRead` property contains the path to the most recently read file. When the ensemble datastore has not yet been read, or has been reset, `LastMemberRead` is an empty string.

When you call `writeToLastMemberRead` to add data back to the ensemble datastore, that function writes to the file specified in `LastMemberRead`.

By default, `read` reads data from one ensemble member at a time (the `ReadSize` property of the ensemble datastore is 1). When `ReadSize > 1`, `LastMemberRead` is a string array containing the paths to all files read in the most recent read operation.

### **Files — List of files in ensemble datastore**

string vector

This property is read-only.

List of files in the ensemble datastore, specified as a column string vector of length `NumMembers`. Each entry contains the full path to a file in the datastore. The files are in the order in which the `read` command reads ensemble members.

Example: ["C:\Data\Data\_01.csv"; "C:\Data\Data\_02.csv"; "C:\Data\Data\_03.csv"]

## **Object Functions**

The `read` and `writeToLastMemberRead` functions are specialized for Predictive Maintenance Toolbox ensemble data. Other functions, such as `reset` and `hasdata`, are identical to those used with `datastore` objects in MATLAB.

<code>read</code>	Read member data from an ensemble datastore
<code>writeToLastMemberRead</code>	Write data to member of an ensemble datastore
<code>reset</code>	Reset datastore to initial state
<code>hasdata</code>	Determine if data is available to read



progress	Determine how much data has been read
numpartitions	Number of datastore partitions
partition	Partition a datastore
tall	Create tall array

## Examples

### Create and Configure File Ensemble Datastore

Create a file ensemble datastore for data stored in MATLAB® files, and configure it with functions that tell the software how to read from and write to the datastore.

For this example, you have two data files containing healthy operating data from a bearing system, `baseline_01.mat` and `baseline_02.mat`. You also have three data files containing faulty data from the same system, `FaultData_01.mat`, `FaultData_02.mat`, and `FaultData_03.mat`. (Because of the volume of data, the unzip operation takes several minutes.) In practice you might have many more data files.

```
unzip fileEnsData.zip % extract compressed files
location = pwd;
extension = '.mat';
fensemble = fileEnsembleDatastore(location,extension);
```

Before you can interact with data in the ensemble, you must create functions that tell the software how to process the data files to read variables into the MATLAB workspace and to write data back to the files. Save these functions to a location on the file path. For this example, use the following supplied functions:

- `readBearingData` — Extract requested variables from a structure, `bearing`, and other variables stored in the file. This function also parses the filename for the fault status of the data. The function returns a table row containing one table variable for each requested variable.
- `writeBearingData` — Take a structure and write its variables to a data file as individual stored variables.

```
addpath(fullfile(matlabroot,'examples','predmaint','main')) % Make sure functions are on path
fensemble.ReadFcn = @readBearingData;
fensemble.WriteToMemberFcn = @writeBearingData;
```

Finally, set properties of the ensemble to identify data variables, condition variables, and selected variables for reading. For this example, the variables in the data file are `gs`, `sr`, `load`, and `rate`. Suppose that you only need to read the fault label, `gs`, and `sr`. Set these variables as the selected variables.

```
fensemble.DataVariables = ["gs";"sr";"load";"rate"];  
fensemble.ConditionVariables = ["label"];  
fensemble.SelectedVariables = ["label";"gs";"sr"];
```

Examine the ensemble. The functions and the variable names are assigned to the appropriate properties.

```
fensemble  
  
fensemble =  
  fileEnsembleDatastore with properties:  
  
          ReadFcn: @readBearingData  
    WriteToMemberFcn: @writeBearingData  
      DataVariables: [4x1 string]  
IndependentVariables: [0x0 string]  
  ConditionVariables: "label"  
  SelectedVariables: [3x1 string]  
        ReadSize: 1  
      NumMembers: 5  
  LastMemberRead: [0x0 string]  
          Files: [5x1 string]
```

These functions that you assigned tell the `read` and `writeToLastMemberRead` commands how to interact with the data files that make up the ensemble. For example, when you call the `read` command, it uses `readBearingData` to read all the variables in `fensemble.SelectedVariables`. For a more detailed example, see “File Ensemble Datastore With Measured Data”.

```
rmpath(fullfile(matlabroot, 'examples', 'predmaint', 'main')) % Reset path
```

### Read from and Write to a File Ensemble Datastore

Create a file ensemble datastore for data stored in MATLAB files, and configure it with functions that tell the software how to read from and write to the datastore. (For more details about configuring file ensemble datastores, see “File Ensemble Datastore With Measured Data”.) Because of the volume of data, the `unzip` operation takes a few minutes.

```

% Create ensemble datastore that points to datafiles in current folder
unzip fileEnsData.zip % extract compressed files
location = pwd;
extension = '.mat';
fensemble = fileEnsembleDatastore(location,extension);

% Specify data and condition variables
fensemble.DataVariables = ["gs";"sr";"load";"rate"];
fensemble.ConditionVariables = "label";

% Configure with functions for reading and writing variable data
addpath(fullfile(matlabroot,'examples','predmaint','main')) % Make sure functions are c
fensemble.ReadFcn = @readBearingData;
fensemble.WriteToMemberFcn = @writeBearingData;

```

The functions tell the `read` and `writeToLastMemberRead` commands how to interact with the data files that make up the ensemble. Thus, when you call the `read` command, it uses `readBearingData` to read all the variables in `fensemble.SelectedVariables`. For this example, `readBearingData` extracts requested variables from a structure, `bearing`, and other variables stored in the file. It also parses the filename for the fault status of the data.

Specify variables to read, and read them from the first member of the ensemble.

```

fensemble.SelectedVariables = ["gs";"load";"label"];
data = read(fensemble)

```

```

data=1x3 table
    label          gs          load
    _____  _____  _____
    "Faulty"     [146484x1 double]    0

```

You can now process the data from the member as needed. For this example, compute the average value of the signal stored in the variable `gs`. Extract the data from the table returned by `read`.

```

gsdata = data.gs{1};
gsmean = mean(gsdata);

```

You can write the mean value `gsmean` back to the data file as a new variable. To do so, first expand the list of data variables in the ensemble to include a variable for the new value. Call the new variable `gsMean`.

```
fensemble.DataVariables = [fensemble.DataVariables; "gsMean"]

fensemble =
    fileEnsembleDatastore with properties:

        ReadFcn: @readBearingData
        WriteToMemberFcn: @writeBearingData
        DataVariables: [5x1 string]
        IndependentVariables: [0x0 string]
        ConditionVariables: "label"
        SelectedVariables: [3x1 string]
        ReadSize: 1
        NumMembers: 5
        LastMemberRead: "C:\TEMP\Bdoc18b_943130_7372\ib632619\14\tpf2dcb597\predmainn
        Files: [5x1 string]
```

Next, write the derived mean value to the file corresponding to the last-read ensemble member. (See “Data Ensembles for Condition Monitoring and Predictive Maintenance”.) When you call `writeToLastMemberRead`, it converts the data to a structure and calls `fensemble.WriteToMemberFcn` to write the data to the file.

```
writeToLastMemberRead(fensemble, 'gsMean', gsmean);
```

Calling `read` again advances the last-read-member indicator to the next file in the ensemble and reads the data from that file.

```
data = read(fensemble)
```

```
data=1x3 table
    label          gs          load
    _____  _____  _____
    "Faulty"      [146484x1 double]      50
```

You can confirm that this data is from a different member by examining the `load` variable in the table. Here, its value is 50, while in the previously read member, it was 0.

You can repeat the processing steps to compute and append the mean for this ensemble member. In practice, it is more useful to automate the process of reading, processing, and writing data. To do so, reset the ensemble to a state in which no data has been read. Then loop through the ensemble and perform the read, process, and write steps for each member.

```

reset(fensemble)
while hasdata(fensemble)
    data = read(fensemble);
    gsdata = data.gs{1};
    gsmean = mean(gsdata);
    writeToLastMemberRead(fensemble, 'gsMean', gsmean);
end

```

The `hasdata` command returns `false` when every member of the ensemble has been read. Now, each data file in the ensemble includes the `gsMean` variable derived from the data `gs` in that file. You can use techniques like this loop to extract and process data from your ensemble files as you develop a predictive-maintenance algorithm. For an example illustrating in more detail the use of a file ensemble datastore in the algorithm-development process, see “Rolling Element Bearing Fault Diagnosis”. The example also shows how to use Parallel Computing Toolbox™ to speed up the processing of large data ensembles.

To confirm that the derived variable is present in the file ensemble datastore, read it from the first and second ensemble members. To do so, reset the ensemble again, and add the new variable to the selected variables. In practice, after you have computed derived values, it can be useful to read only those values without rereading the unprocessed data, which can take significant space in memory. For this example, read selected variables that include the new variable, `gsMean`, but do not include the unprocessed data, `gs`.

```

reset(fensemble)
fensemble.SelectedVariables = ["label"; "load"; "gsMean"];
data1 = read(fensemble)

```

```

data1=1x3 table
    label    load    gsMean
    -----
    "Faulty"    0    -0.23

```

```

data2 = read(fensemble)

```

```

data2=1x3 table
    label    load    gsMean
    -----
    "Faulty"    50    -0.22352

```

```

rmpath(fullfile(matlabroot, 'examples', 'predmaint', 'main')) % Reset path

```

## Compatibility Considerations

### **DataVariablesFcn, IndependentVariablesFcn, and ConditionVariablesFcn properties will be removed**

*Not recommended starting in R2018b*

The DataVariablesFcn, IndependentVariablesFcn, and ConditionVariablesFcn properties will be removed in a future release. Use the ReadFcn property instead.

The ReadFcn property, introduced in R2018b, lets you specify one function to read all variable types from your ensemble datastore. Formerly, you had to designate functions separately for data variables, independent variables, and condition variables. An advantage of using ReadFcn is that the read operation needs to access each member file only once to read all the variables. With separate functions for each variable type, read opens the file up to three times to read all variable types. Thus, designating a single ReadFcn is a more efficient way to access the datastore.

To update your code to use the new property:

- 1 Rewrite your fileEnsembleDatastore read functions into one new function that reads variables of all types. (See “Create and Configure File Ensemble Datastore” on page 2-33 for an example of such a function.)
- 2 Set DataVariablesFcn, IndependentVariablesFcn, and ConditionVariablesFcn to [] to clear them.
- 3 Set ReadFcn to the new function.

## See Also

generateSimulationEnsemble | simulationEnsembleDatastore

## Topics

“Data Ensembles for Condition Monitoring and Predictive Maintenance”

“File Ensemble Datastore With Measured Data”

“File Ensemble Datastore Using Data in Text Files”

**Introduced in R2018a**

# hashSimilarityModel

Hashed-feature similarity model for estimating remaining useful life

## Description

Use `hashSimilarityModel` to estimate the remaining useful life (RUL) of a component using a hashed-feature similarity model. This model is useful when you have run-to-failure degradation path histories for an ensemble of similar components, such as multiple machines manufactured to the same specifications, and the data set is large. The hashed-feature similarity model transforms the historical degradation path data for each ensemble member into a series of *hashed-features*, such as the mean, power, minimum, or maximum values for the data. You can then compute the hashed features of a test component and compare them to the hashed features of the ensemble data members.

To configure a `hashSimilarityModel` object, use `fit`, which computes and stores the hashed feature values of the ensemble data members. Once you configure the parameters of your similarity model, you can then predict the remaining useful life of similar components using `predictRUL`. For similarity models, the RUL of the test component is estimated as the median statistic of the lifetime span of the most similar components minus the current lifetime value of the test component. For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

## Creation

## Syntax

```
mdl = hashSimilarityModel
mdl = hashSimilarityModel(initModel)
mdl = hashSimilarityModel( ____, Name, Value)
```



## Description

`mdl = hashSimilarityModel` creates a hashed-feature similarity model for estimating RUL and initializes the model with default settings.

`mdl = hashSimilarityModel(initModel)` creates a hashed-feature similarity model and initializes the model parameters using an existing `hashSimilarityModel` object `initModel`.

`mdl = hashSimilarityModel( ____, Name, Value)` specifies user-settable model properties using name-value pairs. For example, `hashSimilarityModel('LifeTimeUnit', "days")` creates a hashed-feature similarity model with that uses days as a lifetime unit. You can specify multiple name-value pairs. Enclose each property name in quotes.

## Input Arguments

### **initModel** — Hashed-feature similarity model

`hashSimilarityModel` object

Hashed-feature similarity model, specified as a `hashSimilarityModel` object.

## Properties

### **HashTable** — Hashed feature values

*N*-by-*M* array

This property is read-only.

Hashed feature values generated by the `fit` function, specified as *N*-by-*M* array, where *M* is the number of ensemble members and *N* is the number of hashed features.

`HashTable(i, j)` contains the hashed feature value of *j*th feature computed for the *i*th data member.

To specify the method for computing the hashed features, use the `Method` property of the model.

### **RegimeSplit** — Breakpoints for splitting historical data into multiple regimes

row vector of doubles (default) | [] | row vector of duration objects | row vector of datetime objects

Breakpoints for splitting historical data into multiple regimes, specified as a row vector of double values, `duration` objects, or `datetime` objects. The row vector of breakpoints must:

- Be in increasing order
- Have units and a format that is compatible with the training data used with the `fit` function

To use a single regime, specify `RegimeSplit` as `[]`.

A separate hash table is generated for each regime. The RUL prediction is based on the similarity to the hashed features in the regime to which the test data belongs. If you change the value of `RegimeSplit`, then you must retrain your model using `fit`.

You can specify `RegimeSplit`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **LifeSpan — Ensemble member life spans**

`double vector` (default) | `vector of duration objects`

This property is read-only.

Ensemble member life spans, specified as a `double vector` or `duration` object vector and computed from the ensemble member degradation profiles by the `fit` function.

### **NumNearestNeighbors — Number of nearest neighbors for RUL estimation**

`Inf` (default) | `finite positive integer`

Number of nearest neighbors for RUL estimation, specified as `Inf` or a finite positive integer. If `NumNearestNeighbors` is `Inf`, then `predictRUL` uses all the ensemble members during estimation.

You can specify `NumNearestNeighbors`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Method — Hashed feature computation method**

`"minmaxstd"` (default) | `function handle`

Hashed feature computation method, specified as one of the following:

- "minmaxstd" — Extract the minimum, maximum, and standard deviation of the data. This option omits observations that contain NaN. When you use this method, HashTable is  $M$ -by-3, where  $M$  is the number of ensemble members.
- Function handle — Use a custom function that takes degradation data as a column vector, table, or timetable, and returns a row vector of features. For example:

```
mdl.Method = @(x) [mean(x),std(x),kurtosis(x),median(x)]
```

You can specify Method:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Distance — Distance computation method**

"euclidian" (default) | "absolute" | function handle

Distance computation method, specified as one of the following:

- "euclidian" — Use the 2-norm of the difference between hash vectors.
- "absolute" — Use the 1-norm of the difference between hash vectors.
- Function handle — Use a custom function of the form:

```
D = distanceFunction(xTest,xEnsemble)
```

Here,

- `xTest` is a column vector of length  $N$  that contains test component hashed features, where  $N$  is the number of hashed features.
- `xEnsemble` is an  $M$ -by- $N$  array of ensemble component hashed features, where  $M$  is the number of ensemble components. `xEnsemble(i, :)` contains the hashed features for the  $i$ th ensemble member.
- `D` is a row vector of length  $M$ , where `D(i)` is the distance between the test feature vector and the feature vector of the  $i$ th ensemble member.

You can specify Distance:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **IncludeTies — Flag to include ties**

`true` (default) | `false`

Flag to include ties, specified as `true` or `false`. When `IncludeTies` is `true`, the model includes all neighbors whose distance to the test component data is less than the  $K$ th smallest distance, where  $K$  is equal to `NumNearestNeighbors`.

You can specify `IncludeTies`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Standardize — Flag for standardizing feature data**

`false` (default) | `true`

Flag for standardizing feature data before generating hashed features, specified as `true` or `false`. When `Standardize` is `true`, the feature data is standardized such that feature  $X$  becomes  $(X - \text{mean}(X)) / \text{std}(X)$ .

You can specify `Standardize`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **LifeTimeVariable — Lifetime variable**

`""` (default) | `string`

Lifetime variable, specified as a string that contains a valid MATLAB variable name or `""`.

When you train the model using the `fit` function, if your training data is a:

- `table`, then `LifeTimeVariable` must match one of the variable names in the table
- `timetable`, then `LifeTimeVariable` one of the variable names in the table or the dimension name of the time variable, `data.Properties.DimensionNames{1}`

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

**LifeTimeUnit — Lifetime variable units**`"" (default) | string`

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).

**DataVariables — Degradation variable names**`"" (default) | string | string array`

Degradation variable names, specified as a string or string array. The strings in `DataVariables` must be valid MATLAB variable name.

You can specify `DataVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

**UseParallel — Flag for using parallel computing**`false (default) | true`

Flag for using parallel computing for hash table generation by the `fit` function, specified as either `true` or `false`.

You can specify `UseParallel`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

**UserData — Additional model information**`[] (default) | any data type or format`

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify `UserData`:

- Using a name-value pair when you create the model

- Using dot notation after model creation

## Object Functions

predictRUL	Estimate remaining useful life for a test component
fit	Estimate parameters of remaining useful life model using historical data
compare	Compare test data to historical data ensemble for similarity models

## Examples

### Train Hash Similarity Model

Load training data.

```
load('hashTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create a hash similarity model with default settings. By default, the hashed features used by the model are the signal maximum, minimum, and standard deviation values.

```
mdl = hashSimilarityModel;
```

Train the similarity model using the training data.

```
fit(mdl,hashTrainVectors)
```

### Train Hash Similarity Model Using Tabular Data

Load training data.

```
load('hashTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a hash similarity model that uses the following values as hashed features:

```
mdl = hashSimilarityModel('Method',@(x) [mean(x),std(x),kurtosis(x),median(x)]);
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,hashTrainTables,"Time","Condition")
```

### Predict RUL Using Hash Similarity Model

Load training data.

```
load('hashTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a hash similarity model that uses hours as a life time unit and the following values as hashed features:

- Mean
- Standard deviation
- Kurtosis
- Median

```
mdl = hashSimilarityModel('Method',@(x) [mean(x),std(x),kurtosis(x),median(x)],...  
    'LifeTimeUnit',"hours");
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,hashTrainTables,"Time","Condition")
```

Load testing data. The test data contains the degradation feature measurements for a test component up to the current life time.

```
load('hashTestData.mat')
```

Predict the RUL of the test component using the trained similarity model.

```
estRUL = predictRUL mdl, hashTestData)
```

```
estRUL = duration  
175.69 hr
```

The estimated RUL for the component is around 176 hours.

## Extended Capabilities

### Automatic Parallel Support

Accelerate code by automatically running computation in parallel using Parallel Computing Toolbox™.

To evaluate these models in parallel, set the `UseParallel` property to `true`.

## See Also

### Functions

`fit` | `pairwiseSimilarityModel` | `predictRUL` | `residualSimilarityModel`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**



# linearDegradationModel

Linear degradation model for estimating remaining useful life

## Description

Use `linearDegradationModel` to model a linear degradation process for estimating the remaining useful life (RUL) of a component. Degradation models estimate the RUL by predicting when a monitored signal will cross a predefined threshold. Linear degradation models are useful when the monitored signal is a log scale signal or when the component does not experience cumulative degradation. For more information on the degradation model, see “Linear Degradation Model” on page 2-58.

To configure a `linearDegradationModel` object for a specific type of component, you can:

- Estimate the model prior parameters using historical data regarding the health of an ensemble of similar components, such as multiple machines manufactured to the same specifications. To do so, use `fit`.
- Specify the model prior parameters when you create the model based on your knowledge of the component degradation process.

Once you configure the parameters of your degradation model, you can then predict the remaining useful life of similar components using `predictRUL`. For a basic example illustrating RUL prediction with a degradation model, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

## Creation

## Syntax

```
mdl = linearDegradationModel
```

```
mdl = linearDegradationModel(Name, Value)
```

### Description

`mdl = linearDegradationModel` creates a linear degradation model for estimating RUL and initializes the model with default settings.

`mdl = linearDegradationModel(Name, Value)` specifies user-settable model properties using name-value pairs. For example, `linearDegradationModel('NoiseVariance', 0.5)` creates a linear degradation model with a model noise variance of 0.5. You can specify multiple name-value pairs. Enclose each property name in quotes.

### Properties

#### Theta — Current mean value of slope parameter

scalar

This property is read-only.

Current mean value of slope parameter  $\theta$  in the degradation model, specified as a scalar. For more information on the degradation model, see “Linear Degradation Model” on page 2-58.

You can specify Theta using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of Theta changes when you use the `update` function.

#### ThetaVariance — Current variance of slope parameter

nonnegative scalar

This property is read-only.

Current variance of slope parameter  $\theta$  in the degradation model, specified as a nonnegative scalar. For more information on the degradation model, see “Linear Degradation Model” on page 2-58.

You can specify `ThetaVariance` using a name-value pair argument when you:

- Create the model.
- Reset the model using the `restart` function.

Otherwise, the value of `ThetaVariance` changes when you use the `update` function.

### **Phi — Current intercept value**

scalar

Current intercept value  $\phi$  for the degradation model, specified as a scalar. For more information on the degradation model, see “Linear Degradation Model” on page 2-58.

You can specify `Phi` using a name-value pair argument when you create the model. Otherwise, the value of `Phi` changes when you estimate the model prior using the `fit` function.

### **Prior — Prior information about model parameters**

structure

Prior information about model parameters, specified as a structure with the following fields:

- `Theta` — Mean value of slope parameter
- `ThetaVariance` — Variance of slope parameter

You can specify the fields of `Prior`:

- When you create the model. When you specify `Theta` or `ThetaVariance` at model creation using name-value pairs, the corresponding field of `Prior` is also set.
- Using the `fit` function. In this case, the prior values are derived from the data used to fit the model.
- Using the `restart` function. In this case, the current values of `Theta` and `ThetaVariance` are copied to the corresponding fields of `Prior`.
- Using dot notation after model creation.

For more information on the degradation model, see “Linear Degradation Model” on page 2-58.

### **NoiseVariance — Variance of additive noise**

1 (default) | nonnegative scalar

Variance of additive noise  $\varepsilon$  in the degradation model, specified as a nonnegative scalar. For more information on the degradation model, see “Linear Degradation Model” on page 2-58.

You can specify `NoiseVariance`:

- Using a name-value pair when you create the model
- Using a name-value pair with the `restart` function
- Using dot notation after model creation

### **SlopeDetectionLevel** — Slope detection level

0.05 (default) | scalar value in the range [0,1] | []

Slope detection level for determining the start of the degradation process, specified as a scalar in the range [0,1]. This value corresponds to the alpha value in a t-test of slope significance.

To disable the slope detection test, set `SlopeDetectionLevel` to [].

You can specify `SlopeDetectionLevel`:

- Using a name-value pair when you create the model
- Using a name-value pair with the `restart` function
- Using dot notation after model creation

### **SlopeDetectionInstant** — Slope detection time

[] (default) | scalar

This property is read-only.

Slope detection time, which is the instant when a significant slope is detected, specified as a scalar. The update function sets this value when `SlopeDetectionLevel` is not empty.

### **CurrentMeasurement** — Latest degradation feature value

scalar

This property is read-only.

Latest degradation feature value supplied to the update function, specified as a scalar.

**InitialLifeTimeValue — Initial lifetime variable value**

scalar | duration object

This property is read-only.

Initial lifetime variable value when the `update` function is first called on the model, specified as a scalar.

When the model detects a slope, the `InitialLifeTime` value is changed to match the `SlopeDetectionInstant` value.

**CurrentLifeTimeValue — Current lifetime variable value**

scalar | duration object

This property is read-only.

Latest lifetime variable value supplied to the `update` function, specified as a scalar.

**LifeTimeVariable — Lifetime variable**

"" (default) | string

Lifetime variable, specified as a string that contains a valid MATLAB variable name or "".

When you train the model using the `fit` function, if your training data is a:

- `table`, then `LifeTimeVariable` must match one of the variable names in the table
- `timetable`, then `LifeTimeVariable` one of the variable names in the table or the dimension name of the time variable, `data.Properties.DimensionNames{1}`

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

**LifeTimeUnit — Lifetime variable units**

"" (default) | string

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).

### **DataVariables — Degradation variable name**

`""` (default) | `string`

Degradation variable name, specified as a string that contains a valid MATLAB variable name. Degradation models have only one data variable.

You can specify `DataVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **UseParallel — Flag for using parallel computing**

`false` (default) | `true`

Flag for using parallel computing when fitting prior values from data, specified as either `true` or `false`.

You can specify `UseParallel`:

- Using a name-value pair when you create the model
- Using a name-value pair with the `restart` function
- Using dot notation after model creation

### **UserData — Additional model information**

`[]` (default) | any data type or format

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify `UserData`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

## Object Functions

fit	Estimate parameters of remaining useful life model using historical data
predictRUL	Estimate remaining useful life for a test component
update	Update posterior parameter distribution of degradation remaining useful life model
restart	Reset remaining useful life degradation model

## Examples

### Train Linear Degradation Model

Load training data.

```
load('linTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create a linear degradation model with default settings.

```
mdl = linearDegradationModel;
```

Train the degradation model using the training data.

```
fit(mdl,linTrainVectors)
```

### Create Linear Degradation Model with Known Priors

Create a linear degradation model and configure it with a known prior distribution.

```
mdl = linearDegradationModel('Theta',0.25,'ThetaVariance',0.002);
```

The specified prior distribution parameters are stored in the `Prior` property of the model.

```
mdl.Prior
```

```
ans = struct with fields:  
    Theta: 0.2500
```

```
ThetaVariance: 0.0020
```

The current posterior distribution of the model is also set to match the specified prior distribution. For example, check the posterior value of the slope variance.

```
mdl.ThetaVariance  
ans = 0.0020
```

### Train Linear Degradation Model Using Tabular Data

Load training data.

```
load('linTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a linear degradation model with default settings.

```
mdl = linearDegradationModel;
```

Train the degradation model using the training data. Specify the names of the life time and data variables.

```
fit(mdl, linTrainTables, "Time", "Condition")
```

### Predict RUL Using Linear Degradation Model

Load training data.

```
load('linTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a linear degradation model, specifying the life time variable units.



```
mdl = linearDegradationModel('LifeTimeUnit','hours');
```

Train the degradation model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,linTrainTables,"Time","Condition")
```

Load testing testing data, which is a run-to-failure degradation profile for a test component. The test data is a table with the same life time and data variables as the training data.

```
load('linTestData.mat','linTestData1')
```

Based on knowledge of the degradation feature limits, define a threshold condition indicator value that indicates the end-of-life of a component.

```
threshold = 60;
```

Assume that you measure the component condition indicator after 48 hours. Predict the remaining useful life of the component at this time using the trained linear degradation model. The RUL is the forecasted time at which the degradation feature will pass the specified threshold.

```
estRUL = predictRUL(mdl,linTestData1(48,:),threshold)
```

```
estRUL = duration  
        69.988 hr
```

The estimated RUL is around 70 hours, which indicates a total predicted life span of 118 hours.

### **Update Linear Degradation Model and Predict RUL**

Load observation data.

```
load('linTestData.mat','linTestData1')
```

For this example, assume that the training data is not historical data, but rather real-time observations of the component condition.

Based on knowledge of the degradation feature limits, define a threshold condition indicator value that indicates the end-of-life of a component.

```
threshold = 60;
```

Create a linear degradation model arbitrary prior distribution data and a specified noise variance. Also, specify the life time and data variable names for the observation data.

```
mdl = linearDegradationModel('Theta',1,'ThetaVariance',1e6,'NoiseVariance',0.003,...  
                             'LifeTimeVariable',"Time",'DataVariables',"Condition",...  
                             'LifeTimeUnit',"hours");
```

Observe the component condition for 50 hours, updating the degradation model after each observation.

```
for i=1:50  
    update(mdl,linTestData1(i,:));  
end
```

After 50 hours, predict the RUL of the component using the current life time value stored in the model.

```
estRUL = predictRUL(mdl,threshold)
```

```
estRUL = duration  
        59.406 hr
```

The estimated RUL is about 60 hours, which indicates a total predicted life span of 110 hours.

## Algorithms

### Linear Degradation Model

The `linearDegradationModel` object implements the following continuous-time linear degradation model:

$$S(t) = \phi + \theta(t)t + \varepsilon(t)$$

where:

- $\phi$  is the model intercept, which is constant. You can initialize  $\phi$  as the nominal value of the degradation variable using `Phi`.
- $\theta(t)$  is the model slope and is modeled as a random variable with a normal distribution with mean `Theta` and variance `ThetaVariance`.
- $\varepsilon(t)$  is the model additive noise and is modeled as a normal distribution with zero mean and variance `NoiseVariance`.

## Extended Capabilities

### Automatic Parallel Support

Accelerate code by automatically running computation in parallel using Parallel Computing Toolbox™.

To evaluate these models in parallel, set the `UseParallel` property to `true`.

## See Also

### Functions

`exponentialDegradationModel` | `fit` | `predictRUL` | `update`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**

## **pairwiseSimilarityModel**

Pairwise comparison-based similarity model for estimating remaining useful life

### **Description**

Use `pairwiseSimilarityModel` to estimate the remaining useful life (RUL) of a component using a pairwise comparison-based similarity model. This model compares the degradation profile of a test component directly to the degradation path histories for an ensemble of similar components, such as multiple machines manufactured to the same specifications. The similarity of the test component to the ensemble members is a function of the distance between the degradation profile and the ensemble member profile, which is computed using correlation or dynamic time warping.

To configure a `pairwiseSimilarityModel` object, use `fit`. Once you configure the parameters of your similarity model, you can then predict the remaining useful life of similar components using `predictRUL`. For similarity models, the RUL of the test component is estimated as the median statistic of the lifetime span of the most similar components minus the current lifetime value of the test component. For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

### **Creation**

### **Syntax**

```
mdl = pairwiseSimilarityModel
mdl = pairwiseSimilarityModel(initModel)
mdl = pairwiseSimilarityModel( ____, Name, Value)
```

## Description

`mdl = pairwiseSimilarityModel` creates a pairwise comparison-based similarity model for estimating RUL and initializes the model with default settings.

`mdl = pairwiseSimilarityModel(initModel)` creates a pairwise comparison-based similarity model and initializes the model parameters using an existing `pairwiseSimilarityModel` object `initModel`.

`mdl = pairwiseSimilarityModel( ____, Name, Value)` specifies user-settable model properties using name-value pairs. For example, `hashSimilarityModel('LifeTimeUnit', "days")` creates a pairwise comparison-based similarity model that uses days as a lifetime unit. You can specify multiple name-value pairs. Enclose each property name in quotes.

## Input Arguments

### **initModel** — Pairwise comparison-based similarity model

`pairwiseSimilarityModel` object

Pairwise comparison-based similarity model, specified as a `pairwiseSimilarityModel` object.

## Properties

### **Method** — Time series distance computation method

"correlation" (default) | "dtw"

Time series distance computation method, specified as one of the following:

- "correlation" — Measure distance using correlation
- "dtw" — Compute distance using dynamic time warping. For more information, see `dtw`.

You can specify `Method`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Distance — Distance formula for "dtw"**

"euclidian" (default) | "absolute"

Distance formula for "dtw" distance computation method, specified as one of the following:

- "euclidian" — Use the 2-norm of the difference between residuals.
- "absolute" — Use the 1-norm of the difference between residuals.

You can specify Distance:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **HistorySpan — Lifetime span of historical data**

Inf (default) | positive scalar | duration object

Lifetime span of historical data for computing similarity, specified as a positive scalar or duration object. When computing similarity, the model uses historical data from lifetime ( $t$ -HistorySpan) to lifetime  $t$ , where  $t$  is the current lifetime.

You can specify HistorySpan:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **WithinRangeRatio — Factor determining ensemble member exclusion rule**

1 (default) | scalar from 0 through 1

Factor determining ensemble member exclusion rule for similarity computation, specified as a scalar from 0 through 1. `WithinRangeRatio` is used when the length of the test data and the length of the ensemble member data do not match, which happens near end-of-lifetime values of historical data. When `WithinRangeRatio` is 1, then there is no exclusion of ensemble members.

Suppose that the length of the shorter data is  $P$  and the length of the longer data is  $Q$ . Then, a similarity test is performed only if  $Q(1-\text{WithinRangeRatio}) \leq P \leq Q$ . Otherwise, the ensemble member is ignored.

You can specify `WithinRangeRatio`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

**LifeSpan — Ensemble member life spans**

double vector (default) | vector of duration objects

This property is read-only.

Ensemble member life spans, specified as a double vector or duration object vector and computed from the ensemble member degradation profiles by the fit function.

**NumNearestNeighbors — Number of nearest neighbors for RUL estimation**

Inf (default) | finite positive integer

Number of nearest neighbors for RUL estimation, specified as Inf or a finite positive integer. If NumNearestNeighbors is Inf, then predictRUL uses all the ensemble members during estimation.

You can specify NumNearestNeighbors:

- Using a name-value pair when you create the model
- Using dot notation after model creation

**IncludeTies — Flag to include ties**

true (default) | false

Flag to include ties, specified as true or false. When IncludeTies is true, the model includes all neighbors whose distance to the test component data is less than the Kth smallest distance, where K is equal to NumNearestNeighbors.

You can specify IncludeTies:

- Using a name-value pair when you create the model
- Using dot notation after model creation

**Standardize — Flag for standardizing feature data**

false (default) | true | 'time-varying'

Flag for standardizing feature data before computing distance, specified as true, false, or 'time-varying'.

When `Standardize` is `true`, the feature data is standardized such that feature  $X$  becomes  $(X - \text{mean}(X)) / \text{std}(X)$ .

When `Standardize` is `'time-varying'`, the feature data is standardized such that feature  $X(t)$  becomes  $(X(t) - M(t)) / S(t)$ . Here,  $M(t)$  and  $S(t)$  are running estimates of the mean and standard deviation of the data.

You can specify `Standardize`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **LifeTimeVariable — Lifetime variable**

"" (default) | string

Lifetime variable, specified as a string that contains a valid MATLAB variable name or "".

When you train the model using the `fit` function, if your training data is a:

- `table`, then `LifeTimeVariable` must match one of the variable names in the table
- `timetable`, then `LifeTimeVariable` one of the variable names in the table or the dimension name of the time variable, `data.Properties.DimensionNames{1}`

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **LifeTimeUnit — Lifetime variable units**

"" (default) | string

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).

### **DataVariables — Degradation variable names**

"" (default) | string | string array



Degradation variable names, specified as a string or string array. The strings in `DataVariables` must be valid MATLAB variable names.

You can specify `DataVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **UseParallel — Flag for using parallel computing**

`false` (default) | `true`

Flag for using parallel computing for nearest-neighbor searching, specified as either `true` or `false`.

You can specify `UseParallel`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **UserData — Additional model information**

`[]` (default) | any data type or format

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify `UserData`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

## **Object Functions**

<code>predictRUL</code>	Estimate remaining useful life for a test component
<code>fit</code>	Estimate parameters of remaining useful life model using historical data
<code>compare</code>	Compare test data to historical data ensemble for similarity models

## **Examples**

### Train Pairwise Similarity Model

Load training data.

```
load('pairwiseTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create a pairwise similarity model with default settings.

```
mdl = pairwiseSimilarityModel;
```

Train the similarity model using the training data.

```
fit(mdl,pairwiseTrainVectors)
```

### Train Pairwise Similarity Model Using Tabular Data

Load training data.

```
load('pairwiseTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a pairwise similarity model that computes distance using dynamic time warping with an absolute distance metric.

```
mdl = pairwiseSimilarityModel('Method','dtw','Distance','absolute');
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,pairwiseTrainTables,"Time","Condition")
```

### Predict RUL Using Pairwise Similarity Model

Load training data.

```
load('pairwiseTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a pairwise similarity model that computes distance using dynamic time warping with an absolute distance metric and uses hours as a life time unit.

```
mdl = pairwiseSimilarityModel('Method','dtw','Distance','absolute','LifeTimeUnit','hours')
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,pairwiseTrainTables,"Time","Condition")
```

Load testing data. The test data contains the degradation feature measurements for a test component up to the current life time.

```
load('pairwiseTestData.mat')
```

Predict the RUL of the test component using the trained similarity model.

```
estRUL = predictRUL(mdl,pairwiseTestData)
```

```
estRUL = duration  
    93.671 hr
```

The estimated RUL for the component is around 94 hours.

## Extended Capabilities

### Automatic Parallel Support

Accelerate code by automatically running computation in parallel using Parallel Computing Toolbox™.

To evaluate these models in parallel, set the `UseParallel` property to `true`.

## See Also

### Functions

`fit` | `hashSimilarityModel` | `predictRUL` | `residualSimilarityModel`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**

# reliabilitySurvivalModel

Probabilistic failure-time model for estimating remaining useful life

## Description

Use `reliabilitySurvivalModel` to estimate the remaining useful life (RUL) of a component using a probability distribution of component failure times. Reliability survival models are useful when the only data you have are the failure times for an ensemble of similar components, such as multiple machines manufactured to the same specifications.

To configure a `reliabilitySurvivalModel` object for a specific type of component, use `fit`, which estimates the probability distribution coefficients from a collection of failure-time data. Once you configure the parameters of your reliability survival model, you can then predict the remaining useful life of similar components using `predictRUL`. For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

## Creation

## Syntax

```
mdl = reliabilitySurvivalModel
mdl = reliabilitySurvivalModel(distribution)
mdl = reliabilitySurvivalModel(initModel)
mdl = reliabilitySurvivalModel( ____, Name, Value)
```

## Description

`mdl = reliabilitySurvivalModel` creates a reliability survival model for estimating RUL model that uses a Weibull distribution and initializes the model with default settings.

`mdl = reliabilitySurvivalModel(distribution)` creates a reliability survival model that uses the specified probability distribution function and sets the `Distribution` property of the model.

`mdl = reliabilitySurvivalModel(initModel)` creates a reliability survival model and initializes the model parameters using an existing `reliabilitySurvivalModel` object `initModel`.

`mdl = reliabilitySurvivalModel( ____, Name, Value)` specifies user-settable model properties using name-value pairs. For example, `reliabilitySurvivalModel('LifeTimeUnit', 'days')` creates a reliability survival model that uses days as a lifetime unit. You can specify multiple name-value pairs. Enclose each property name in quotes.

### Input Arguments

#### **initModel** — Reliability survival model

`reliabilitySurvivalModel` object

Reliability survival model, specified as a `reliabilitySurvivalModel` object.

### Properties

#### **Distribution** — Probability distribution function

"Weibull" (default) | "Normal" | "Poisson" | "Kernel" | "Rayleigh" | "Gamma" | ...

Probability distribution function used to model the lifetime distribution, specified as one of the following:

Distribution String	Distribution Object
"BirnbaumSaunders"	BirnbaumSaundersDistribution
"Exponential"	ExponentialDistribution
"Gamma"	GammaDistribution
"GeneralizedPareto"	GeneralizedParetoDistribution
"HalfNormal"	HalfNormalDistribution
"InverseGaussian"	InverseGaussianDistribution

Distribution String	Distribution Object
"Kernel"	KernelDistribution
"Logistic"	LogisticDistribution
"Loglogistic"	LoglogisticDistribution
"Lognormal"	LognormalDistribution
"Nakagami"	NakagamiDistribution
"Normal"	NormalDistribution
"Poisson"	PoissonDistribution
"Rayleigh"	RayleighDistribution
"Stable"	StableDistribution
"Weibull"	WeibullDistribution

To configure the parameters of the probability distribution function, use the `fit` function.

#### **ParameterValues — Distribution coefficients**

vector

This property is read-only.

Distribution coefficients estimated by the `fit` function, specified as a vector. For more information on the coefficients of each distribution function, see the corresponding distribution object listed in `Distribution`. For more information on model fitting, see `fitdist`.

#### **ParameterCovariance — Covariance of the distribution coefficients**

array

This property is read-only.

Covariance of the distribution coefficients estimated by the `fit` function, specified as a positive array with size equal to the number of coefficients. For more information on the coefficients of each distribution function, see the corresponding distribution object listed in `Distribution`.

#### **ParameterNames — Distribution coefficient names**

string array

This property is read-only.

Distribution coefficient names assigned when the model is trained using the `fit` function, specified as string array. For more information on the coefficients of each distribution function, see the corresponding distribution object listed in [Distribution](#).

### **CensorVariable — Censor variable**

"" (default) | string

Censor variable, specified as a string that contains a valid MATLAB variable name. The censor variable is a binary variable that indicates which life-time measurements in data are not end-of-life values.

`CensorVariable` must not match any of the strings in `DataVariables` or `LifeTimeVariable`.

You can specify `CensorVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **LifeTimeVariable — Lifetime variable**

"" (default) | string

Lifetime variable, specified as a string that contains a valid MATLAB variable name. For survival models, the lifetime variable contains the historical life span measurements of components.

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Manually using dot notation

### **LifeTimeUnit — Lifetime variable units**

"" (default) | string

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).



**DataVariables — Data variables**

"" (default)

Data variables, specified as an empty string. This property is ignored for reliability survival models.

**UserData — Additional model information**

[] (default) | any data type or format

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify UserData:

- Using a name-value pair when you create the model
- Using dot notation after model creation

**Object Functions**

predictRUL Estimate remaining useful life for a test component

fit Estimate parameters of remaining useful life model using historical data

**Examples****Train Reliability Survival Model**

Load training data.

```
load('reliabilityData.mat')
```

This data is a column vector of duration objects representing battery discharge times.

Create a reliability survival model with default settings.

```
mdl = reliabilitySurvivalModel;
```

Train the survival model using the training data.

```
fit(mdl,reliabilityData,"hours")
```

### **Predict RUL Using Reliability Survival Model and View PDF**

Load training data.

```
load('reliabilityData.mat')
```

This data is a column vector of duration objects representing battery discharge times.

Create a reliability survival model, specifying the life time variable and life time units.

```
mdl = reliabilitySurvivalModel('LifeTimeVariable',"DischargeTime",'LifeTimeUnit',"hours")
```

Train the survival model using the training data.

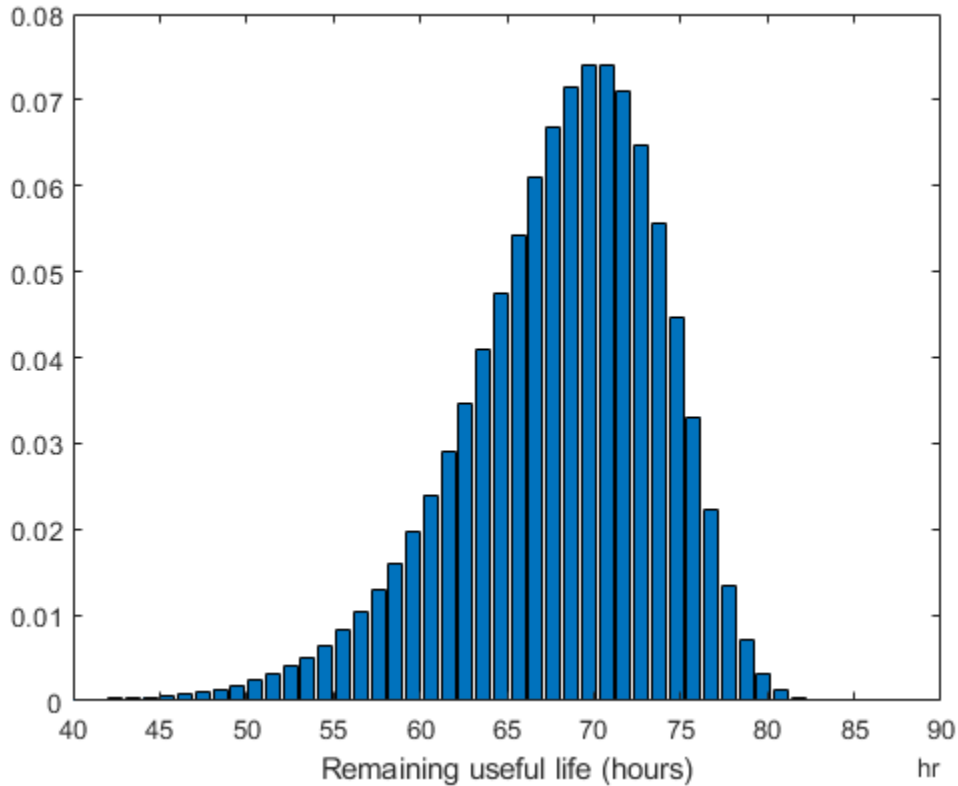
```
fit(mdl,reliabilityData)
```

Predict the life span of a new component, and obtain the probability distribution function for the estimate.

```
[estRUL,ciRUL,pdfRUL] = predictRUL(mdl);
```

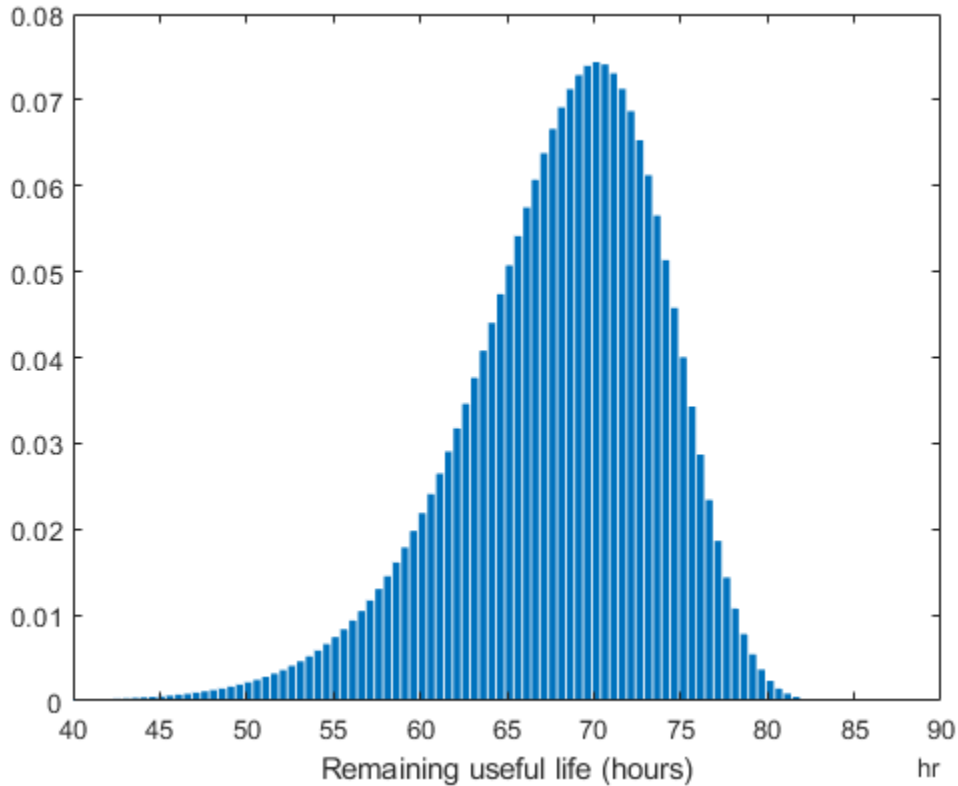
Plot the probability distribution.

```
bar(pdfRUL.RUL,pdfRUL.ProbabilityDensity)  
xlabel('Remaining useful life (hours)')  
xlim(hours([40 90]))
```



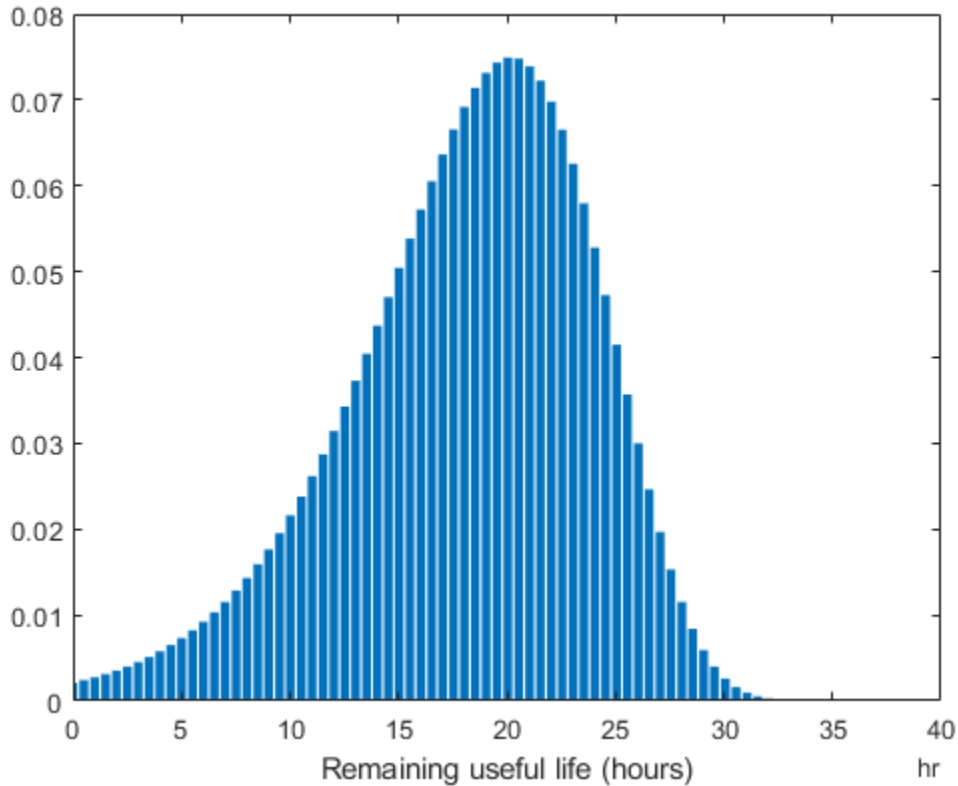
Improve the distribution view by providing the number of bins and bin size for the prediction.

```
[estRUL,ciRUL,pdfRUL] = predictRUL mdl, 'BinSize',0.5, 'NumBins',500);  
bar(pdfRUL.RUL,pdfRUL.ProbabilityDensity)  
xlabel('Remaining useful life (hours)')  
xlim(hours([40 90]))
```



Predict the RUL for a component that has been operating for 50 hours.

```
[estRUL,ciRUL,pdfRUL] = predictRUL mdl, hours(50), 'BinSize', 0.5, 'NumBins', 500);  
bar(pdfRUL.RUL,pdfRUL.ProbabilityDensity)  
xlabel('Remaining useful life (hours)')  
xlim(hours([0 40]))
```



## See Also

### Functions

`covariateSurvivalModel` | `fit` | `predictRUL`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**

# residualSimilarityModel

Residual comparison-based similarity model for estimating remaining useful life

## Description

Use `residualSimilarityModel` to estimate the remaining useful life (RUL) of a component using a residual comparison-based similarity model. This model is useful when you have degradation profiles for an ensemble of similar components, such as multiple machines manufactured to the same specifications, and you know the dynamics of the degradation process. The historical data for each member of the data ensemble is fitted with a model of identical structure. The degradation data of the test component is used to compute 1-step prediction errors, or residuals, for each ensemble model. The magnitudes of these errors indicate how similar the test component is to the corresponding ensemble members.

To configure a `residualSimilarityModel` object, use `fit`, which trains and stores the degradation model for each data ensemble member. Once you configure the parameters of your similarity model, you can then predict the remaining useful life of similar components using `predictRUL`. For similarity models, the RUL of the test component is estimated as the median statistic of the lifetime span of the most similar components minus the current lifetime value of the test component. For a basic example illustrating RUL prediction, see “Update RUL Prediction as Data Arrives”.

For general information on predicting remaining useful life, see “Models for Predicting Remaining Useful Life”.

## Creation

## Syntax

```
mdl = residualSimilarityModel
mdl = residualSimilarityModel(initModel)
mdl = residualSimilarityModel( ____,Name,Value)
```

## Description

`mdl = residualSimilarityModel` creates a residual comparison-based similarity model for estimating RUL and initializes the model with default settings.

`mdl = residualSimilarityModel(initModel)` creates a residual comparison-based similarity model and initializes the model parameters using an existing `residualSimilarityModel` object `initModel`.

`mdl = residualSimilarityModel( ____, Name, Value)` specifies user-settable model properties using name-value pairs. For example, `hashSimilarityModel('LifeTimeUnit', "days")` creates a residual comparison-based similarity model that uses days as a lifetime unit. You can specify multiple name-value pairs. Enclose each property name in quotes.

## Input Arguments

### **initModel** — Residual comparison-based similarity model

`residualSimilarityModel` object

Residual comparison-based similarity model, specified as a `residualSimilarityModel` object.

## Properties

### **Method** — Type of model

"arma2" (default) | "linear" | "arima2" | "poly2" | "exp1" | ...

Type of model trained using the `fit` function and used for residual generation, specified as one of the following:

- "linear" — Line with offset term
- "poly2" — Second-order polynomial
- "poly3" — Third-order polynomial
- "exp1" — Exponential with offset term
- "exp2" — Sum of two exponentials
- "arma2" — Second-order ARMA model



- "arma3" — Third-order ARMA model
- "arima2" — Second-order ARMA model with noise integration
- "arima3" — Third-order ARMA model with noise integration

Select the model type based on your knowledge of the dynamics of the component degradation process.

You can specify **Method**:

- Using a name-value pair when you create the model
- Using dot notation after model creation

For more information on estimating ARMA and polynomial models, see `armax` and `polyfit`, respectively.

### **Distance — Distance computation method**

"euclidian" (default) | "absolute" | function handle

Distance computation method, specified as one of the following:

- "euclidian" — Use the 2-norm of the residual signal.
- "absolute" — Use the 1-norm of the residual signal.
- Function handle — Use a custom function of the form:

```
D = distanceFunction(r)
```

where,

- `r` is the residual, specified as a column vector.
- `D` is the distance, returned as nonnegative scalar.

You can specify **Distance**:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Models — Parameters of the fitted models**

cell array

This property is read-only.

Parameters of the fitted models for each member of the training data ensemble, specified as a cell array and assigned by the `fit` function. The content of `Models` depends on the type of model used for regression, as specified in `Method`.

Method	Model Structure	Models Cell Content
"linear"	$at + b$	Row vector — $[a \ b]$
"poly2"	$at^2 + bt + c$	Row vector — $[a \ b \ c]$
"poly3"	$at^3 + bt^2 + ct + d$	Row vector — $[a \ b \ c \ d]$
"exp1"	$ae^{bt}+c$	Row vector — $[a \ b \ c]$
"exp2"	$ae^{bt}+ce^{dt}$	Row vector — $[a \ b \ c \ d]$
"arma2"	<p>Second-order ARMA model:</p> $A(q)S(t) = C(q)e(t)$ <p>where</p> <ul style="list-style-type: none"> <li>• <math>A(q) = [1 \ a_1q^{-1} \ a_2q^{-2}]</math></li> <li>• <math>C(q) = [1 \ c_1q^{-1}]</math></li> <li>• <math>S(t)</math> is the degradation feature</li> </ul>	<p>Structure with fields:</p> <ul style="list-style-type: none"> <li>• A — Row vector <math>[1 \ a_1 \ a_2]</math></li> <li>• C — Row vector <math>[1 \ c_1]</math></li> </ul>
"arma3"	Similar to "arma2", but with $A(q)$ third-order and $C(q)$ second-order	<p>Structure with fields:</p> <ul style="list-style-type: none"> <li>• A — Row vector <math>[1 \ a_1 \ a_2 \ a_3]</math></li> <li>• C — Row vector <math>[1 \ c_1 \ c_2]</math></li> </ul>
"arima2"	<p>Similar to "arma2", but with an additional noise integrator:</p> $A(q)S(t) = \frac{C(q)}{1-q^{-1}}e(t)$	<p>Structure with fields:</p> <ul style="list-style-type: none"> <li>• A — Row vector <math>[1 \ a_1 \ a_2]</math></li> <li>• C — Row vector <math>[1 \ c_1]</math></li> </ul>
"arima3"	Similar to "arma3", but with an additional noise integrator	<p>Structure with fields:</p> <ul style="list-style-type: none"> <li>• A — Row vector <math>[1 \ a_1 \ a_2 \ a_3]</math></li> <li>• C — Row vector <math>[1 \ c_1 \ c_2]</math></li> </ul>

For more information on estimating ARMA and polynomial models, see `armax` and `polyfit`, respectively.

### **ModelMSE — Mean squared error of the estimation for each model**

vector

This property is read-only.

Mean squared error of the estimation for each model in `Models`, specified as a vector and assigned by the `fit` function.

### **LifeSpan — Ensemble member life spans**

double vector (default) | vector of duration objects

This property is read-only.

Ensemble member life spans, specified as a double vector or duration object vector and computed from the ensemble member degradation profiles by the `fit` function.

### **NumNearestNeighbors — Number of nearest neighbors for RUL estimation**

Inf (default) | finite positive integer

Number of nearest neighbors for RUL estimation, specified as `Inf` or a finite positive integer. If `NumNearestNeighbors` is `Inf`, then `predictRUL` uses all the ensemble members during estimation.

You can specify `NumNearestNeighbors`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **IncludeTies — Flag to include ties**

true (default) | false

Flag to include ties, specified as `true` or `false`. When `IncludeTies` is `true`, the model includes all neighbors whose distance to the test component data is less than the  $K$ th smallest distance, where  $K$  is equal to `NumNearestNeighbors`.

You can specify `IncludeTies`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **Standardize — Flag for standardizing residuals**

`false` (default) | `true`

Flag for standardizing residuals before computing distance, specified as `true` or `false`.

When `Standardize` is `true`, the residuals are scaled by the inverse square root of the estimated mean squared errors in `ModelMSE`.

You can specify `Standardize`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **LifeTimeVariable — Lifetime variable**

`""` (default) | string

Lifetime variable, specified as a string that contains a valid MATLAB variable name or `""`.

When you train the model using the `fit` function, if your training data is a:

- `table`, then `LifeTimeVariable` must match one of the variable names in the table
- `timetable`, then `LifeTimeVariable` one of the variable names in the table or the dimension name of the time variable, `data.Properties.DimensionNames{1}`

You can specify `LifeTimeVariable`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **LifeTimeUnit — Lifetime variable units**

`""` (default) | string

Lifetime variable units, specified as a string.

The units of the lifetime variable do not need to be time-based. The life of the test component can be measured in terms of a usage variable, such as distance traveled (miles) or fuel consumed (gallons).

### **DataVariables — Degradation variable names**

`""` (default) | string | string array

Degradation variable names, specified as a string or string array. The strings in `DataVariables` must be valid MATLAB variable names.

You can specify `DataVariables`:

- Using a name-value pair when you create the model
- As an argument when you call the `fit` function
- Using dot notation after model creation

### **UseParallel — Flag for using parallel computing**

`false` (default) | `true`

Flag for using parallel computing for nearest-neighbor searching, specified as either `true` or `false`.

You can specify `UseParallel`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

### **UserData — Additional model information**

`[]` (default) | any data type or format

Additional model information for bookkeeping purposes, specified as any data type or format. The model does not use this information.

You can specify `UserData`:

- Using a name-value pair when you create the model
- Using dot notation after model creation

## **Object Functions**

<code>predictRUL</code>	Estimate remaining useful life for a test component
<code>fit</code>	Estimate parameters of remaining useful life model using historical data
<code>compare</code>	Compare test data to historical data ensemble for similarity models

## **Examples**

### Train Residual Similarity Model

Load training data.

```
load('residualTrainVectors.mat')
```

The training data is a cell array of column vectors. Each column vector is a degradation feature profile for a component.

Create a residual similarity model with default settings.

```
mdl = residualSimilarityModel;
```

Train the similarity model using the training data.

```
fit(mdl,residualTrainVectors)
```

### Train Residual Similarity Model Using Tabular Data

Load training data.

```
load('residualTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a residual similarity model that fits the data with a third-order ARMA model and uses an absolute distance metric.

```
mdl = residualSimilarityModel('Method','arma3','Distance','absolute');
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,residualTrainTables,"Time","Condition")
```

### Predict RUL Using Residual Similarity Model

Load training data.

```
load('residualTrainTables.mat')
```

The training data is a cell array of tables. Each table is a degradation feature profile for a component. Each profile consists of life time measurements in the "Time" variable and corresponding degradation feature measurements in the "Condition" variable.

Create a residual similarity model that fits the data with a third-order ARMA model and uses hours as the life time unit.

```
mdl = residualSimilarityModel('Method','arma3','LifeTimeUnit','hours');
```

Train the similarity model using the training data. Specify the names of the life time and data variables.

```
fit(mdl,residualTrainTables,"Time","Condition")
```

Load testing data. The test data contains the degradation feature measurements for a test component up to the current life time.

```
load('residualTestData.mat')
```

Predict the RUL of the test component using the trained similarity model.

```
estRUL = predictRUL(mdl,residualTestData)
```

```
estRUL = duration  
      85.73 hr
```

The estimated RUL for the component is around 86 hours.

## Extended Capabilities

### Automatic Parallel Support

Accelerate code by automatically running computation in parallel using Parallel Computing Toolbox™.

To evaluate these models in parallel, set the `UseParallel` property to `true`.

## See Also

### Functions

`fit` | `hashSimilarityModel` | `pairwiseSimilarityModel` | `predictRUL`

### Topics

“Update RUL Prediction as Data Arrives”

“RUL Estimation Using RUL Estimator Models”

**Introduced in R2018a**



# simulationEnsembleDatastore

Manage ensemble data generated by `generateSimulationEnsemble` or by logging simulation data in Simulink

## Description

A `simulationEnsembleDatastore` object is a datastore specialized for use in developing algorithms for condition monitoring and predictive maintenance using simulated data.

This object specifies the data variables, independent variables, and condition variables stored in a collection of MATLAB data files (MAT-files). The data files contain `Simulink.SimulationData.Dataset` variables that are the result of logging data during Simulink model simulation.

For a detailed example illustrating the use of a simulated ensemble datastore, see “Generate and Use Simulated Data Ensemble”. For general information about data ensembles in Predictive Maintenance Toolbox, see “Data Ensembles for Condition Monitoring and Predictive Maintenance”.

## Creation

To create a `simulationEnsembleDatastore` object:

- 1 Generate and log simulation data from a Simulink model. You can do so using `generateSimulationEnsemble` or any other means of logging simulation to disk.
- 2 Create a `simulationEnsembleDatastore` object that points to the generated simulation data using the `simulationEnsembleDatastore` command (described below).

If you have simulation data previously generated with `generateSimulationEnsemble` or other means, you can use the creation function `simulationEnsembleDatastore` to create a new simulation ensemble datastore object at any time.

## Syntax

```
ensemble = simulationEnsembleDatastore(location)
ensemble = simulationEnsembleDatastore(location,signallog)
ensemble = simulationEnsembleDatastore(location,signallog,
Name,Value)
```

## Description

`ensemble = simulationEnsembleDatastore(location)` creates a simulation ensemble from data previously generated using `generateSimulationEnsemble` in the folder specified by `location`. The function identifies ensemble variables in the generated data from information stored in the generated MAT-files. The function populates the `DataVariables` and `SelectedVariables` properties of `ensemble` with the names of these ensemble variables.

`ensemble = simulationEnsembleDatastore(location,signallog)` uses `signallog` to determine which variable in the MAT-files contains logged signals. Use the variable name specified in the `Signal logging` configuration parameter of the Simulink model from which the data is generated. Specifying this variable allows the ensemble to treat those signals as ensemble data variables, rather than the `signallog` variable itself. The other variables in the MAT-file are also returned as ensemble data variables.

`ensemble = simulationEnsembleDatastore(location,signallog, Name,Value)` specifies additional properties on page 2-91 of the object using one or more name-value pair arguments. For example, using `'IndependentVariables'`, `["Age"; "ID"]` specifies the independent variables when you create the object.

## Input Arguments

### location — File path

string | character vector

File path to the location in which to store simulation data, specified as a string or a character vector. The file path can be any location supported by MATLAB datastores, including an IRI path pointing to a remote location. However, when you use a `simulationEnsembleDatastore` to manage remote data, you cannot use `writeToLastMemberRead` to add data to the ensemble datastore. For more information about working with remote data in MATLAB, see “Work with Remote Data” (MATLAB)

Example: `pwd + "\simResults"`

### **signallog** — Variable name of logged signals

string | character vector

Variable name of logged signals, specified as a string or a character vector. This input argument tells `simulationEnsembleDatastore` which data variable in the stored MAT-files contains the logged simulation data. This variable name is specified in the `SignalLogging` configuration parameter of the Simulink model from which the data is generated. When you use `generateSimulationEnsemble` to generate simulation data for the ensemble, each generated MAT-file contains a variable, `PMSignalLogName`, specifying the variable name of the logged signals.

Example: `"logout"`

## **Properties**

### **DataVariables** — Data variables in the ensemble

string array of logged signal names (default) | string array

Data variables in the ensemble, specified as a string array. Data variables are the main content of the members of an ensemble. Data variables can include measured data or derived data for analysis and development of predictive maintenance algorithms. For example, your data variables might include measured or simulated vibration signals and derived values such as mean vibration value or peak vibration frequency. In practice, your data variables, independent variables, and condition variables are all distinct sets of variables.

`simulationEnsembleDatastore` sets the initial value of `DataVariables` to the names of all the logged signals in the data generated `generateSimulationEnsemble`.

You can also specify `DataVariables` using a cell array of character vectors, such as `{'Vibration'; 'Tacho'}`, but the variable names are always stored as a string array, `["Vibration"; "Tacho"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **IndependentVariables** — Independent variables in the ensemble

[] (default) | string array

Independent variables in the ensemble, specified as a string array. You typically use independent variables to order the members of an ensemble. Examples are timestamps,

number of operating hours, or miles driven. Set this property to the names of such variables in your ensemble. In practice, your data variables, independent variables, and condition variables are all distinct sets of variables.

You can also specify `IndependentVariables` using a cell array of character vectors, such as `{'Time'; 'Age'}`, but the variable names are always stored as a string array, `["Time"; "Age"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **ConditionVariables — Condition variables in the ensemble**

`[]` (default) | string array

Condition variables in the ensemble, specified as a string array. Use condition variables to label the members in an ensemble according to the fault condition or other operating condition under which the ensemble member was collected. In practice, your data variables, independent variables, and condition variables are all distinct sets of variables.

You can also specify `ConditionVariables` using a cell array of character vectors, such as `{'GearFault'; 'Temperature'}`, but the variable names are always stored as a string array, `["GearFault"; "Temperature"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

### **SelectedVariables — Variables to read**

string array of logged signal names (default) | string array

Variables to read from the ensemble, specified as a string array. Use this property to specify which variables are extracted to the MATLAB workspace when you use the `read` command to read data from the ensemble. `read` returns a table row containing a table variable for each name specified in `SelectedVariables`. For example, suppose that you have an ensemble, `ensemble`, that contains six variables, and you want to read only two of them, `Vibration` and `FaultState`. Set the `SelectedVariables` property and call `read`.

```
ensemble.SelectedVariables = ["Vibration"; "FaultState"];  
data = read(ensemble)
```

`SelectedVariables` can be any combination of the variables in the `DataVariables`, `ConditionVariables`, and `IndependentVariables` properties. If `SelectedVariables` is empty, `read` generates an error.

`simulationEnsembleDatastore` sets the initial value of `SelectedVariables` to the names of all the logged signals in the data generated by `generateSimulationEnsemble`.

You can specify `SelectedVariables` using a cell array of character vectors, such as `{'Vibration'; 'Tacho'}`, but the variable names are always stored as a string array, `["Vibration"; "Tacho"]`. If you specify a matrix of variable names, the matrix is flattened to a column vector.

**ReadSize — Number of members to read**

1 (default) | positive integer

Number of members to read from the ensemble datastore at once, specified as a positive integer that is smaller than the total number of members in the ensemble. By default, the `read` command returns a one-row table containing data from one ensemble member. To read data from multiple members in a single read operation, set this property to an integer value greater than one. For example, if `ReadSize = 3`, then `read` returns a three-row table where each row contains data from a different ensemble member. If fewer than `ReadSize` members are unread, then `read` returns a table with as many rows as there are remaining members.

The ensemble datastore property `LastMemberRead` contains the names of all files read during the most recent read operation. Thus, for instance, if `ReadSize = 3`, then a read operation sets `LastMemberRead` to a string vector containing three file names.

When you use `writeToLastMemberRead`, specify the data to write as a table with a number of rows equal to `ReadSize`. The `writeToLastMemberRead` command updates the members specified by `LastMemberRead`, writing one table row to each specified file.

Changing the `ReadSize` property also resets the ensemble to its unread state. For instance, suppose that you read some ensemble members one at a time (`ReadSize = 1`), and then change `ReadSize` to 3. The next read operation returns data from the first three ensemble members.

**NumMembers — Number of members in ensemble**

positive integer

This property is read-only.

Number of members in the ensemble, specified as a positive integer.

**LastMemberRead — File name of last ensemble member read**

"" (default) | string | string array

This property is read-only.

File name of last ensemble member read into the MATLAB workspace, specified as a string. When you use the `read` command to read data from an ensemble datastore, the software determines which ensemble member to read next, and reads data from the corresponding file. The `LastMemberRead` property contains the path to the most recently read file. When the ensemble datastore has not yet been read, or has been reset, `LastMemberRead` is an empty string.

When you call `writeToLastMemberRead` to add data back to the ensemble datastore, that function writes to the file specified in `LastMemberRead`.

By default, `read` reads data from one ensemble member at a time (the `ReadSize` property of the ensemble datastore is 1). When `ReadSize > 1`, `LastMemberRead` is a string array containing the paths to all files read in the most recent `read` operation.

### Files — List of files in ensemble datastore

string vector

This property is read-only.

List of files in the ensemble datastore, specified as a column string vector of length `NumMembers`. Each entry contains the full path to a file in the datastore. The files are in the order in which the `read` command reads ensemble members.

Example: ["C:\Data\Data\_01.csv"; "C:\Data\Data\_02.csv"; "C:\Data\Data\_03.csv"]

## Object Functions

The `read` and `writeToLastMemberRead` functions are specialized for Predictive Maintenance Toolbox ensemble data. Other functions, such as `reset` and `hasdata`, are identical to those used with `datastore` objects in MATLAB.

<code>read</code>	Read member data from an ensemble datastore
<code>writeToLastMemberRead</code>	Write data to member of an ensemble datastore
<code>reset</code>	Reset datastore to initial state
<code>hasdata</code>	Determine if data is available to read
<code>progress</code>	Determine how much data has been read
<code>numpartitions</code>	Number of datastore partitions
<code>partition</code>	Partition a datastore
<code>tall</code>	Create tall array

## Examples

### Generate Ensemble of Fault Data

Generate a simulation ensemble datastore of data representing a machine operating under fault conditions by simulating a Simulink® model of the machine while varying a fault parameter.

Load the Simulink model. This model is a simplified version of the gear-box model described in “Using Simulink to Generate Fault Data”. For this example, only one fault mode is modeled, a gear-tooth fault.

```
mdl = 'TransmissionCasingSimplified';
open_system(mdl)
```

The gear-tooth fault is modeled as a disturbance in the Gear Tooth fault subsystem. The magnitude of the disturbance is controlled by the model variable `ToothFaultGain`, where `ToothFaultGain = 0` corresponds to no gear-tooth fault (healthy operation). To generate the ensemble of fault data, you use `generateSimulationEnsemble` to simulate the model at different values of `ToothFaultGain`, ranging from -2 to zero. This function uses an array of `Simulink.SimulationInput` objects to configure the Simulink model for each member in the ensemble. Each simulation generates a separate member of the ensemble in its own data file. Create such an array, and use `setVariable` to assign a tooth-fault gain value for each run.

```
toothFaultValues = -2:0.5:0; % 5 ToothFaultGain values

for ct = numel(toothFaultValues):-1:1
    simin(ct) = Simulink.SimulationInput(mdl);
    simin(ct) = setVariable(simin(ct), 'ToothFaultGain', toothFaultValues(ct));
end
```

For this example, the model is already configured to log certain signal values, `Vibration` and `Tacho` (see “Export Signal Data Using Signal Logging” (Simulink)). `generateSimulationEnsemble` further configures the model to:

- Save logged data to files in the folder you specify.
- Use the `timetable` format for signal logging.
- Store each `Simulink.SimulationInput` object in the saved file with the corresponding logged data.

Specify a location for the generated data. For this example, save the data to a folder called `Data` within your current folder. The indicator `status` is 1 (true) if all the simulations complete without error.

```
mkdir Data
location = fullfile(pwd, 'Data');
[status,E] = generateSimulationEnsemble(simin,location);

[27-Aug-2018 14:27:56] Running SetupFcn...
[27-Aug-2018 14:27:56] Running simulations...
[27-Aug-2018 14:28:51] Completed 1 of 5 simulation runs
[27-Aug-2018 14:29:01] Completed 2 of 5 simulation runs
[27-Aug-2018 14:29:10] Completed 3 of 5 simulation runs
[27-Aug-2018 14:29:18] Completed 4 of 5 simulation runs
[27-Aug-2018 14:29:28] Completed 5 of 5 simulation runs
```

Inside the `Data` folder, examine one of the files. Each file is a MAT-file containing the following MATLAB® variables:

- `SimulationInput` — The `Simulink.SimulationInput` object that was used to configure the model for generating the data in the file. You can use this to extract information about the conditions (such as faulty or healthy) under which this simulation was run.
- `logout` — A `Dataset` object containing all the data that the Simulink model is configured to log.
- `PMSignalLogName` — The name of the variable that contains the logged data ('`logout`' in this example). The `simulationEnsembleDatastore` command uses this name to parse the data in the file.
- `SimulationMetadata` — Other information about the simulation that generated the data logged in the file.

Now you can create the simulation ensemble datastore using the generated data. The resulting `simulationEnsembleDatastore` object points to the generated data. The object lists the data variables in the ensemble, and by default all the variables are selected for reading. Examine the `DataVariables` and `SelectedVariables` properties of the ensemble to confirm these designations.

```
ensemble = simulationEnsembleDatastore(location)

ensemble =
    simulationEnsembleDatastore with properties:
```



```

        DataVariables: [4x1 string]
IndependentVariables: [0x0 string]
    ConditionVariables: [0x0 string]
        SelectedVariables: [4x1 string]
            ReadSize: 1
            NumMembers: 5
        LastMemberRead: [0x0 string]
            Files: [5x1 string]

```

#### `ensemble.DataVariables`

```

ans = 4x1 string array
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"

```

#### `ensemble.SelectedVariables`

```

ans = 4x1 string array
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"

```

You can now use `ensemble` to read and analyze the generated data in the ensemble datastore. See `simulationEnsembleDatastore` for more information.

### **Extract Subset of Stored Variables from Ensemble Member**

In general, you use the `read` command to extract data from a `simulationEnsembleDatastore` object into the MATLAB® workspace. Often, your ensemble contains more variables than you need to use for a particular analysis. Use the `SelectedVariables` property of the `simulationEnsembleDatastore` object to select a subset of variables for reading.

For this example, use the following code to create a `simulationEnsembleDatastore` object using data previously generated by running a Simulink® model at a various fault values (See `generateSimulationEnsemble`). The ensemble includes simulation data

for five different values of a model parameter, `ToothFaultGain`. Because of the volume of data, the `unzip` operation takes a few minutes.

```
unzip simEnsData.zip % extract compressed files
ensemble = simulationEnsembleDatastore(pwd, 'logout')
```

```
ensemble =
  simulationEnsembleDatastore with properties:

    DataVariables: [5x1 string]
  IndependentVariables: [0x0 string]
    ConditionVariables: [0x0 string]
    SelectedVariables: [5x1 string]
      ReadSize: 1
      NumMembers: 5
    LastMemberRead: [0x0 string]
      Files: [5x1 string]
```

The model that generated the data, `TransmissionCasingSimplified`, was configured such that the resulting ensemble contains variables including accelerometer data, `Vibration`, and tachometer data, `Tacho`. By default, the `simulationEnsembleDatastore` object designates all these variables as both data variables and selected variables, as shown in the `DataVariables` and `SelectedVariables` properties.

`ensemble.DataVariables`

```
ans = 5x1 string array
    "PMSignalLogName"
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
```

`ensemble.SelectedVariables`

```
ans = 5x1 string array
    "PMSignalLogName"
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
```

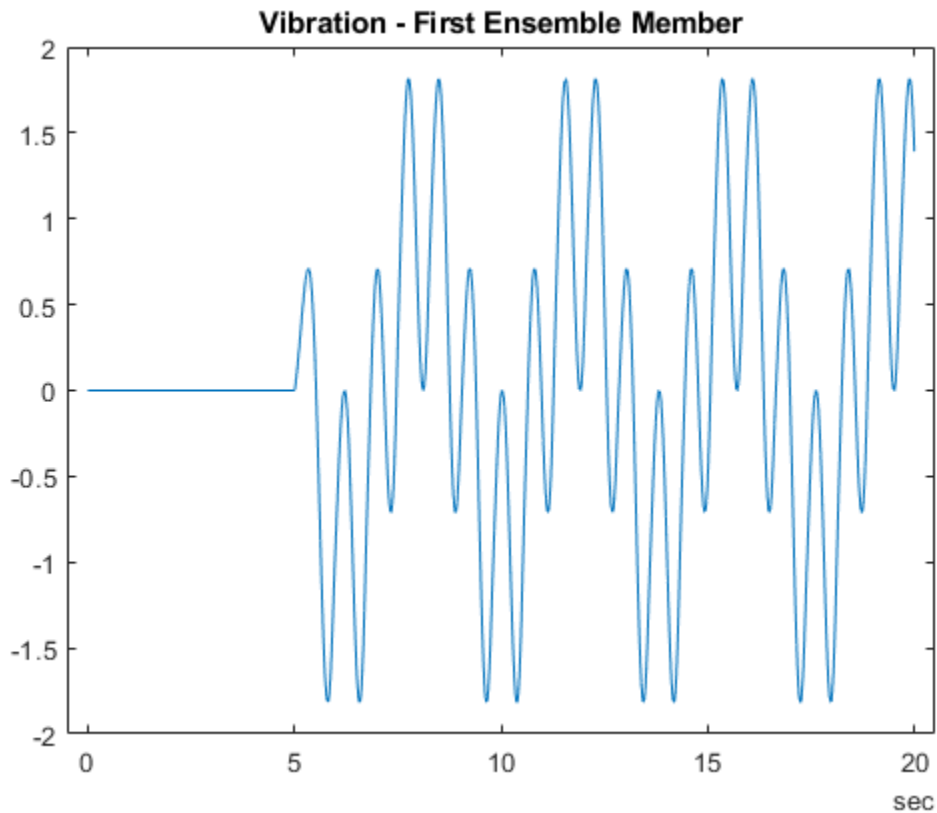
Suppose that for the analysis you want to do, you need only the `Vibration` data and the `Simulink.SimulationInput` object that describes the conditions under which this member data was simulated. Set `ensemble.SelectedVariables` to specify the variables you want to read. The `read` command then extracts those variables from the current ensemble member.

```
ensemble.SelectedVariables = ["Vibration";"SimulationInput"];  
data1 = read(ensemble)
```

```
data1=1x2 table  
      Vibration      SimulationInput  
-----  
[20202x1 timetable]  [1x1 Simulink.SimulationInput]
```

`data.Vibration` is a cell array containing one `timetable` that stores the simulation times and the corresponding vibration signal. You can now process this data as needed. For instance, extract the vibration data from the table and plot it.

```
vibdata1 = data1.Vibration{1};  
plot(vibdata1.Time,vibdata1.Data)  
title('Vibration - First Ensemble Member')
```



The next time you call `read` on this ensemble, the last-read member designation advances to the next member of the ensemble (see “Data Ensembles for Condition Monitoring and Predictive Maintenance”). Read the selected variables from the next member of the ensemble.

```
data2 = read(ensemble)
```

```
data2=1x2 table
```

```
Vibration
```

```
SimulationInput
```

---

```
[20215x1 timetable]
```

---

```
[1x1 Simulink.SimulationInput]
```

To confirm that `data1` and `data2` contain data from different ensemble members, examine the values of the varied model parameter, `ToothFaultGain`. For each ensemble, this value is stored in the `Variables` field of the `SimulationInput` variable.

```
data1.SimulationInput{1}.Variables
```

```
ans =  
  Variable with properties:  
  
      Name: 'ToothFaultGain'  
      Value: -2  
  Workspace: 'global-workspace'
```

```
data2.SimulationInput{1}.Variables
```

```
ans =  
  Variable with properties:  
  
      Name: 'ToothFaultGain'  
      Value: -1.5000  
  Workspace: 'global-workspace'
```

This result confirms that `data1` is from the ensemble member with `ToothFaultGain = -2`, and `data2` is from the member with `ToothFaultGain = -1.5`.

## Append Derived Data to Ensemble Members

You can process data in an ensemble datastore and add derived variables to the ensemble members. For this example, process a variable value to compute a label that indicates whether the ensemble member contains data obtained with a fault present. You then add that label to the ensemble.

For this example, use the following code to create a `simulationEnsembleDatastore` object using data previously generated by running a Simulink® model at a various fault values. (See `generateSimulationEnsemble`.) The ensemble includes simulation data for five different values of a model parameter, `ToothFaultGain`. The model was configured to log the simulation data to a variable named `logout` in the MAT-files that are stored for this example in `simEnsData.zip`. Because of the volume of data, the `unzip` operation might take a minute or two.

```
unzip simEnsData.zip % extract compressed files
ensemble = simulationEnsembleDatastore(pwd, 'logsout')
```

```
ensemble =
  simulationEnsembleDatastore with properties:
```

```
    DataVariables: [5x1 string]
  IndependentVariables: [0x0 string]
    ConditionVariables: [0x0 string]
    SelectedVariables: [5x1 string]
        ReadSize: 1
        NumMembers: 5
    LastMemberRead: [0x0 string]
        Files: [5x1 string]
```

Read the data from the first member in the ensemble. The software determines which ensemble is the first member, and updates the property `ensemble.LastMemberRead` to reflect the name of the corresponding file.

```
data = read(ensemble)
```

```
data=1x5 table
  PMSignalLogName      SimulationInput      SimulationMetadata
-----
  'logsout'           [1x1 Simulink.SimulationInput]  [1x1 Simulink.SimulationMetada
```

By default, all the variables stored in the ensemble data are designated as `SelectedVariables`. Therefore, the returned table row includes all ensemble variables, including a variable `SimulationInput`, which contains the `Simulink.SimulationInput` object that configured the simulation for this ensemble member. That object includes the `ToothFaultGain` value used for the ensemble member, stored in a data structure in its `Variables` property. Examine that value. (For more information about how the simulation configuration is stored, see `Simulink.SimulationInput`.)

```
data.SimulationInput{1}
```

```
ans =
  SimulationInput with properties:

    ModelName: 'TransmissionCasingSimplified'
```

```

    InitialState: [0x0 Simulink.SimState.ModelSimState]
    ExternalInput: []
    ModelParameters: [0x0 Simulink.Simulation.ModelParameter]
    BlockParameters: [0x0 Simulink.Simulation.BlockParameter]
        Variables: [1x1 Simulink.Simulation.Variable]
    PreSimFcn: []
    PostSimFcn: []
    UserString: ''

```

```

Inputvars = data.SimulationInput{1}.Variables;
Inputvars.Name

```

```

ans =
'ToothFaultGain'

```

```

Inputvars.Value

```

```

ans = -2

```

Suppose that you want to convert the `ToothFaultGain` values for each ensemble member into a binary indicator of whether or not a tooth fault is present. Suppose further that you know from your experience with the system that tooth-fault gain values less than 0.1 in magnitude are small enough to be considered healthy operation. Convert the gain value for this ensemble into an indicator that is 0 (no fault) for  $-0.1 < \text{gain} < 0.1$ , and 1 (fault) otherwise.

```

sT = abs(Inputvars.Value) < 0.1;

```

To append the new tooth-fault indicator to the corresponding ensemble data, first expand the list of data variables in the ensemble to include a variable for the indicator.

```

ensemble.DataVariables = [ensemble.DataVariables; "ToothFault"];
ensemble.DataVariables

```

```

ans = 6x1 string array
    "PMSignalLogName"
    "SimulationInput"
    "SimulationMetadata"
    "Tacho"
    "Vibration"
    "ToothFault"

```

This operation is conceptually equivalent to adding a column to the table of ensemble data. Now that `DataVariables` contains the new variable name, assign the derived value to that column of the member using `writeToLastMemberRead`.

```
writeToLastMemberRead(ensemble, 'ToothFault', sT);
```

In practice, you want to append the tooth-fault indicator to every member in the ensemble. To do so, reset the ensemble datastore to its unread state, so that the next read operation starts at the first ensemble member. Then, loop through all the ensemble members, computing `ToothFault` for each member and appending it. The reset operation does not change `ensemble.DataVariables`, so `"ToothFault"` is still present in that list.

```
reset(ensemble);
```

```
sT = false;
while hasdata(ensemble)
    data = read(ensemble);
    InputVars = data.SimulationInput{1}.Variables;
    TFGain = InputVars.Value;
    sT = abs(TFGain) < 0.1;
    writeToLastMemberRead(ensemble, 'ToothFault', sT);
end
```

Finally, designate the new tooth-fault indicator as a condition variable in the ensemble datastore. You can use this designation to track and refer to variables in the ensemble data that represent conditions under which the member data was generated.

```
ensemble.ConditionVariables = {"ToothFault"};
ensemble.ConditionVariables
```

```
ans =
    "ToothFault"
```

You can add the new variable to `ensemble.SelectedVariables` when you want to read it out for further analysis. For an example that shows more ways to manipulate and analyze data stored in a `simulationEnsembleDatastore` object, see [“Using Simulink to Generate Fault Data”](#).



## Read Multiple Ensemble Members in One Operation

To read data from multiple ensemble members in one call to the `read` command, use the `ReadSize` property of an ensemble datastore. This example uses `simulationEnsembleDatastore`, but you can use the same technique for `fileEnsembleDatastore`.

Use the following code to create a `simulationEnsembleDatastore` object using data previously generated by running a Simulink model at a various fault values (see `generateSimulationEnsemble`). The ensemble includes simulation data for five different values of a model parameter, `ToothFaultGain`. (Because of the volume of data, the unzip operation might take a minute or two.) Specify some of the data variables to read.

```
unzip simEnsData.zip % extract compressed files
ensemble = simulationEnsembleDatastore(pwd, 'logout');
ensemble.SelectedVariables = ["Vibration"; "SimulationInput"];
```

By default, calling `read` on this ensemble datastore returns a single-row table containing the values of the `Vibration` and `SimulationInput` variables for the first ensemble member. Change the `ReadSize` property to read three members at once.

```
ensemble.ReadSize = 3;
data1 = read(ensemble)
```

```
data1=3x2 table
      Vibration      SimulationInput
-----
[20202x1 timetable] [1x1 Simulink.SimulationInput]
[20215x1 timetable] [1x1 Simulink.SimulationInput]
[20204x1 timetable] [1x1 Simulink.SimulationInput]
```

`read` returns a three-row table, where each row contains data from one of the first, second, and third ensemble members. `read` also updates the `LastReadMember` property of the ensemble datastore to a string array containing the paths of the three corresponding files. Avoid setting `ReadSize` to a value so large as to risk running out of memory while loading the data.

If the ensemble contains three or more additional members, the next `read` operation returns data from the fourth, fifth, and sixth members. Because the ensemble of this example contains only five members total, the next `read` operation returns only two rows.

```
data2 = read(ensemble)
```

```
data2=2x2 table
```

```
    Vibration
```

```
    SimulationInput
```

---

```
[20213x1 timetable]
```

```
[20224x1 timetable]
```

---

```
[1x1 Simulink.SimulationInput]
```

```
[1x1 Simulink.SimulationInput]
```

## See Also

`fileEnsembleDatastore` | `generateSimulationEnsemble`

## Topics

“Generate and Use Simulated Data Ensemble”

“Data Ensembles for Condition Monitoring and Predictive Maintenance”

**Introduced in R2018a**