Package ‘EEMDelm’

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CEEMDANelm

Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise Based ELM Model

Description

The CEEMDANelm function computes forecasted value with different forecasting evaluation criteria for Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise based Extreme Learning Machine model.

Usage

CEEMDANelm(data, stepahead=10, num.IMFs=emd_num_imfs(length(data)), s.num=4L, num.sift=50L, ensem.size=250L, noise.st=0.2)

Arguments

data: Input univariate time series (ts) data.
stepahead: The forecast horizon.
num.IMFs: Number of Intrinsic Mode Function (IMF) for input series.
s.num: Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
num.sift: Number of siftings to find out IMFs.
ensem.size: Number of copies of the input signal to use as the ensemble.
noise.st: Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.

Details

Some useless IMFs are generated in EMD and EEMD, which degrades performance of these algorithms. Therefore, reducing the number of these useless IMFs is advantageous for improving the computation efficiency of these techniques. Torres et al.(2011) proposed CEEMDAN. Fewer IMFs may be generated on the premise of successfully separating different components of a series by using this algorithm, which can reduce the computational cost.

Value

TotalIMF: Total number of IMFs.
AllIMF: List of all IMFs with residual for input series.
data_test: Testing set is used to measure the out of sample performance.
AllIMF_forecast: Forecasted value of all individual IMF.
FinalCEEMDANELM_forecast
Final forecasted value of the CEEMDANELM model. It is obtained by combining the forecasted value of all individual IMF.

MAE_CEEMDANELM
Mean Absolute Error (MAE) for CEEMDANELM model.

MAPE_CEEMDANELM
Mean Absolute Percentage Error (MAPE) for CEEMDANELM model.

rmse_CEEMDANELM
Root Mean Square Error (RMSE) for CEEMDANELM model.

References

See Also
EMDelm, EEMDELM

Examples

```r
data("Data_Soybean")
CEEMDANelm(Data_Soybean)
```

Data_Soybean

<table>
<thead>
<tr>
<th>Monthly International Soybean Oil Price</th>
</tr>
</thead>
</table>

Description

Monthly international Soyabean oil price from August 2001 to June 2020.

Usage

```r
data("Data_Soybean")
```

Format

A time series data with 227 observations.

price a time series
Details

Dataset contains 227 observations of monthly international Soyabean oil price. It is obtained from World Bank "Pink sheet".

Source


References


Examples

data(Data_Soybean)

EEMDELM

Ensemble Empirical Mode Decomposition Based ELM Model

Description

The EEMDelm function computes forecasted value with different forecasting evaluation criteria for Ensemble Empirical Mode Decomposition based Extreme Learning Machine model.

Usage

EEMDELM(data, stepahead=10,
num.IMFs=emd_num_imfs(length(data)), s.num=4L,
num.sift=50L, ensem.size=250L, noise.st=0.2)

Arguments

data Input univariate time series (ts) data.
stepahead The forecast horizon.
num.IMFs Number of Intrinsic Mode Function (IMF) for input series.
s.num Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
num.sift Number of siftings to find out IMFs.
ensem.size Number of copies of the input signal to use as the ensemble.
noise.st Standard deviation of the Gaussian random numbers used as additional noise. This value is relative to the standard deviation of the input series.
Details
To overcome the problem of EMD (i.e. mode mixing), Ensemble Empirical Mode Decomposition (EEMD) method was developed by Wu and Huang (2009), which significantly reduces the chance of mode mixing and represents a substantial improvement over the original EMD.

Value
- **Total IMF**: Total number of IMFs.
- **All IMF**: List of all IMFs with residual for input series.
- **data_test**: Testing set is used to measure the out of sample performance.
- **All IMF_forecast**: Forecasted value of all individual IMF.
- **FinalEEMDELM_forecast**: Final forecasted value of the EEMDELM model. It is obtained by combining the forecasted value of all individual IMF.
- **MAE_EEMDELM**: Mean Absolute Error (MAE) for EEMDELM model.
- **MAPE_EEMDELM**: Mean Absolute Percentage Error (MAPE) for EEMDELM model.
- **rmse_EEMDELM**: Root Mean Square Error (RMSE) for EEMDELM model.

References

See Also
- EMDelm, CEEMDANelm

Examples
```r
data("Data_Soybean")
EEMDELM(Data_Soybean)
```
The EMDelm function computes forecasted value with different forecasting evaluation criteria for Empirical Mode Decomposition based Extreme Learning Machine model.

Usage

EMDelm(xt, stepahead = 10, s.num = 4L, num.sift = 50L)

Arguments

xt Input univariate time series (ts) data.
stepahead The forecast horizon.
s.num Integer. Use the S number stopping criterion for the EMD procedure with the given values of S. That is, iterate until the number of extrema and zero crossings in the signal differ at most by one, and stay the same for S consecutive iterations.
num.sift Number of siftings to find out IMFs.

Details

This function decomposes the original time series into several independent intrinsic mode functions (IMFs) and one residual component (Huang et al., 1998). Then extreme learning machine, a class of feedforward neural network is used to forecast these IMFs and residual component individually (Huang et al., 2006). Finally, the prediction results of all IMFs including residual are aggregated to formulate an ensemble output for the original time series.

Value

TotalIMF Total number of IMFs.
AllIMF List of all IMFs with residual for input series.
data_test Testing set is used to measure the out of sample performance.
AllIMF_forecast Forecasted value of all individual IMF.
FinalEMDELM_forecast Final forecasted value of the EMDELM model. It is obtained by combining the forecasted value of all individual IMF.
MAE_EMDELM Mean Absolute Error (MAE) for EMDELM model.
MAPE_EMDELM Mean Absolute Percentage Error (MAPE) for EMDELM model.
rmse_EMDELM Root Mean Square Error (RMSE) for EMDELM model.
EMDelm

References


See Also

EEMDELM, CEEMDANelm

Examples

data("Data_Soybean")
EMDelm(Data_Soybean)
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