Signal reconstruction – An alternative approach for wind turbine monitoring

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Content

1. Monitoring wind turbine signals
2. Normal behaviour models
3. Data for analysis
4. Neural networks & stochastic approach
5. Results
6. Conclusions & outlook
1. Monitoring signals

Motivation
- Cost effective evaluation of wind turbine health

Utilisation
- Difference between measurements and expected behaviour is investigated to detect anomalies

Development
- 'Normal behaviour' models are created using available signals (with neural networks)

Monitoring wind turbine vibration
Based on SCADA data (Zhang, 2012)
2. Normal behaviour model

Motivation
- Can we use the stochastic approach to develop a suitable normal behaviour model?

Methodology
- Investigate tower top acceleration with wind speed. Use data from turbine AV04
- Create a 'normal behaviour' model with neural network
- Repeat process with stochastic approach
- Compare models, response & report out
3. Data for analysis

- Wind turbine AV04
- Target signal: tower top acceleration (a)
- Predictor signal: wind speed (v)
- Data sets:
  - Development – October 2014
  - Test – November 2014
- Presented signals are normalised

Example of velocity (v) and acceleration (a)
3. Data for analysis

- Wind turbine AV04
- Target signal: tower top acceleration \((a)\)
- Predictor signal: wind speed \((v)\)
- Data sets:
  - Development – October 2014
  - Test – November 2014
- 1 Hz sampling data

Example of velocity \((v)\) and acceleration \((a)\)
4. Models development

Velocity $v(t)$

Acceleration $a(t)$

Model Development

Parameters

AV 04 – Oct. 2014
4. Models development

Velocity $v(t)$

Acceleration $a(t)$

AV 04 – Oct. 2014

Model Development

Parameters

Neural network

Linear part $w$

Non-linear part $f(), h()$

Steady part $D1$

Transient part $D2$

Stochastic approach
4. Models development

\[ \hat{y}(x, w) = f \left( \sum_{j=0}^{n_h} \omega_j h \left( \sum_{i=0}^{n_i} \omega_i x_i \right) \right) \]

Neural network

- Linear part \( w \)
- Non-linear part \( f(), h() \)
- Steady part \( D1 \)
- Transient part \( D2 \)

\[ \frac{dx}{dt} = D^{(1)}(x) + \sqrt{D^{(2)}(x)} \Gamma_t \]

AV 04 – Oct. 2014
4. Models prediction

Velocity \( v(t) \)

Measurement \( a(t) \)

Model Available

Prediction \( \hat{a}(t) \)

Neural network

Stochastic approach

AV 04 – Nov. 2014
5. Results

- Stochastic approach better estimates distribution moments (4th → non-gaussian)
- Neural networks reconstructs a Gaussian, original signal is non-gaussian
5. Results

- Reconstructed signals have similar average response
- Neural networks reconstruction does not reproduce frequency content
- Stochastic approach better reconstructs variance in signal
- Frequency content is maintained with stochastic approach
6. Conclusions & outlook

- The stochastic approach is suitable to create normal behaviour models
- Both methodologies follow similar steps to construct models
- Neural networks reconstruct central part of original signal
- Stochastic approach better reconstructs complete frequency content

→ Stochastic approach available for R: https://cran.r-project.org/web/packages/Langevin/
→ Analysis will be extended for different sampling ratios
→ Complete procedure & results will be published
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Other results

- Evaluation of bias an variance
- Mean absolute error (MAE)
- Standard deviation of (SD of MAE)

→ Reconstructed signals have similar average response
→ Stochastic approach better reconstructs variance from original signal

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \\
\text{SD of AE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( |\hat{y}_i - y_i| - \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \right)^2}
\]

<table>
<thead>
<tr>
<th>Approach</th>
<th>MAE [%]</th>
<th>SD of MAE [%]</th>
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</thead>
<tbody>
<tr>
<td>Neural network</td>
<td>0.0312</td>
<td>0.0315</td>
</tr>
<tr>
<td>Stochastic</td>
<td>0.0266</td>
<td>0.0305</td>
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</tbody>
</table>
### Other results

<table>
<thead>
<tr>
<th>Approach</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skew</th>
<th>Kurtosis</th>
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</thead>
<tbody>
<tr>
<td>Measurements</td>
<td>-0.0021</td>
<td>0.0267</td>
<td>0.0206</td>
<td>8.8910</td>
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<tr>
<td>Neural network</td>
<td>0.0029</td>
<td>0.0308</td>
<td>0.2139</td>
<td>0.1057</td>
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<tr>
<td>Stochastic</td>
<td>-0.0016</td>
<td>0.0249</td>
<td>-0.0009</td>
<td>3.1993</td>
</tr>
</tbody>
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Inter step differences

\[ \frac{\Delta a}{\sigma_{\Delta a}} \]