DDDAS: A Framework for the Dynamic Data-Driven Fault Diagnosis of Wind Turbine Systems

CMMI – 0540132 (Texas A&M University)  PI: Yu Ding (IE)
CMMI – 0540278 (University of Connecticut)  PI: Jiong Tang (ME)
Students: Eunshin Byon, Chiwoo Park (TAMU)
               Yi Lu, Xin Wang (UConn)
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Background

• Wind energy
  ▪ Pollution free, fastest growing energy source
  ▪ Enough wind energy in the U.S. to produce three times as much electricity as the U.S. uses now

• Current situation and cost
  ▪ Today wind generates less than 0.5% of US electricity
  ▪ Class 6 sites (average wind speeds of 6.7 m/s at 10 m height) can market electricity at 3 to 4 c/kWh – can compete with traditional energy source after tax credit (1.7c/kWh); New class 6 sites becoming less available
  ▪ Current emphasis is on Class 4 sites (5.8 m/s at 10 m height) that cover large area - 20 times the developable wind resource of Class 6 sites; cost at 5 to 6 c/kWh – goal is to reduce cost to 3c/kWh

• Major hurdle
  ▪ High maintenance cost and failure caused down time
Wind Turbine System

- Extremely complicated system
  - Blades up to 70m long
  - Many gear stages to speed up
- Operate under non-steady condition
- Operate in remote area
- Maintenance
  - Mobilization of crane $60,000
  - Crew of 12 in 3 day $15,000
- Failure...
- Low speed wind turbine has longer blades and more complex gearbox
Challenges and Current Limitation in Wind Turbine Health Monitoring

- Need a highly sensitive, robust, and autonomous health monitoring system
  - Reduce maintenance cost
  - Reduce failure-caused down time
  - Reduce false alarms

- Challenges
  - Extreme complexity of the system
  - Non-steady operation and large uncertainty/noise

- Existing methods and limitation
  - Sensory system is fixed and incomplete (only recording gearbox vibration signals – black-box in airplane)
  - Non-dynamic and non-robust signal processing and feature extraction
  - Modeling approach is rigid – pure mechanistic models or neural network
Dynamic Data-Driven Framework for Wind Turbine Diagnosis

- Re-configurable sensory network: fixed sensors and wireless/mobile sensors
- Data-driven pre-processing modules: adaptive feature extraction and sensor anomaly removal
- Multi-level models, incorporating historical data and on-line signals into modeling/prediction
- Dynamic interrogation strategy: action taken according to current conditions
Blade Local Detection: Wave propagation Based Approach

- **Lamb waves**
  - elastic guided waves propagating in a solid layer with free boundaries
  - highly sensitive to **local** discontinuities – compared to global, vibration based methods
  - conveniently generated and sensed by piezoelectric transducers embedded in wind turbine blades – in situ damage detection

- **Damage detection system**
  - undamaged blade
  - damaged blade: mode conversion, phase change, frequency shift, etc.

- wave propagation patterns have noticeable difference, but subject to noise/uncertainty in wind turbine operations
Current Practices

How to differentiate damaged signals from healthy signals?

- Feature extraction and de-noising
  - time-domain analysis or spectral analysis (Fourier transform)
  - joint time-frequency analysis (continuous/discrete wavelet transforms). Haar, Daubechies, Mexican hat, Gabor, Morlet: **choice of wavelets is not always clear**
  - de-noising: local and/or global averaging, filtering

- Decision making
  - uncertainty/variation/noise addressed through root-mean-square deviation (RMSD), mean absolute percentage deviation (MAPD), covariance (Cov) and correlation coefficient (CC)

Current practice limitations

- ad hoc methods requiring human interpretation/intervention – no systematic way of dealing with noise/uncertainty
- decision making is not quantitative – confidence level?
Blade Local Interrogation: New Approach

- **Objective** – develop a robust and quantitative approach for blade local interrogation using piezo transducers

- **Integrated methodology** – three inter-related components
  - adaptive harmonic wavelet transform (AHWT)
    - data-driven feature extraction
  - principal component analysis (PCA) based truncation procedure
    - feature highlighting and denoising
    - *handle multiple signals when embedded into AHWT*
  - Hotelling’s $T^2$ analysis
    - eliminate outliers from the baseline
    - *confidence level-based decision making under PCA based feature highlighting*

- **Method is generic** – can be directly extended to data-driven monitoring of gearbox transient vibration
New Approach Overview

Baseline signals, $L = 5$

AHWT basis

Wavelet coefficients

Common wavelet basis

(Subgrouping, $K=3$)

Minimum total entropy

Remove corresponding baseline signal

Test signal

Hotelling's $T^2$

Damaged

Yes

Larger than $UCL_1$?

Undamaged

No

Larger than $UCL_2$?

Quantitative Decision Making

Feature Extraction

Feature Highlighting Denoising

Robust Signal Processing and Local Decision Making
Adaptive Harmonic Wavelet Transform

- **Harmonic wavelet transform**
  - each level \((m, n)\) corresponds to one frequency range \((m2\pi, n2\pi)\).
    
    \[
    W_{mnk}(\omega) = \begin{cases} 
    \frac{1}{(n-m)2\pi} e^{-i\omega \frac{k}{n-m}} & m2\pi \leq \omega \leq n2\pi \\
    0 & \text{otherwise}
    \end{cases}
    \]
    
    \[
    w_{mnk}(t) = w_{mn}(t - \frac{k}{n-m}) = \frac{\exp\left[\text{i}n2\pi(t - \frac{k}{n-m})\right] - \exp\left[\text{i}m2\pi(t - \frac{k}{n-m})\right]}{(n-m)i2\pi t}
    \]
  
  - easy interpretation - signal analysis is carried out in *specific frequency bands associated with known physical meanings*
  
  - flexibility in selecting level parameters \(m\) and \(n\)
  
  - computational efficiency - coefficients can be calculated using FFT

- **Adaptive harmonic wavelet transform** (Liu, 2003)
  
  - treat each selection \(\{(m_0, n_0), (m_1, n_1), \ldots, (m_{L-1}, n_{L-1})\}\) as a partition of \(\Omega = \{0, 1, \ldots, N_f\}\)
Data-Driven Feature Extraction

- Shannon entropy-based algorithm
  \[ H(x) = -\sum_j p_j \log p_j \quad \text{where} \quad p_j = \frac{|x_j|^2}{\|x\|^2} \]
- search a (e.g. binary) partition tree for the best wavelet basis, giving sparsest representation of the signal

- Improved AHWT for multi-signal applications
  - since AHWT is data-driven, multiple signals from the same healthy blade may lead to different ‘best’ wavelet bases
    - total Shannon entropy
      \[ H(A_i) = H(a_1) + H(a_2) + \cdots + H(a_L) \]
    - select the common wavelet basis \( \{w_{mnk}\}_u \) for the baseline dataset
      \[ u = \operatorname{arg\,min}_l H(A_l) \]
Feature Extraction Example

AHWT versus discrete/continuous Daubechies 4
### Robust Signal Processing and Local Decision Making

#### New Approach Overview

<table>
<thead>
<tr>
<th>Baseline signals, $L = 5$</th>
<th>AHWT basis</th>
<th>Wavelet coefficients</th>
<th>Common wavelet basis</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>${w_{mnk}}$</td>
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<td>(Subgrouping, $K=3$)</td>
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<td></td>
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<td>PCA denoising</td>
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</tbody>
</table>

- Remove corresponding baseline signal
- Yes: larger than $UCL_1$?
  - Yes
  - Damaged
  - No: larger than $UCL_2$?
    - Yes:Damaged
    - No: Undamaged
Feature Highlighting and De-Nosing

- Principal component analysis (PCA)
  - transforms a number of correlated variables into a *reduced* vector space
  - implemented by singular value decomposition (SVD)
- Denoising by PCA truncation
  - the first principal component (PC) accounts for major variation, and each succeeding PC explains as much of the remaining variability as possible
  - noise can be reduced by eliminating the information not contained in the first few principal components
  - percentage truncation threshold $ET\%$

$$rk_0 = \min rk$$

$$s.t. \sum_{j=1}^{rk} \lambda_j > ET\% \sum_{j=1}^{K} \lambda_j$$

Features are further highlighted in the joint time-frequency domain.
New Approach Overview

Robust Signal Processing and Local Decision Making
Quantitative Decision Making

- Hotelling’s $T^2$ analysis – deal with **normal variation** under multiple baseline measurements
  - Phase I: baseline self-checking
    \[ T^2_i = (\hat{x}_i - \hat{\mu})\hat{C}^{-1}(\hat{x}_i - \hat{\mu})^T \]
    - $T^2$ follows the F-distribution
    - Phase I upper control limit:
    \[ UCL^1_{K,L,\alpha} = \frac{K(L-1)^2}{L(L-K)} F_{\alpha} (K, L-K) \]
    - purify the baseline dataset by eliminating outliers
  - Phase II: decision making for damage detection
    - Phase II upper control limit – updated due to new on-line measurement
    \[ UCL^2_{K,L,\alpha} = \frac{K(L-1)(L+1)}{L(L-K)} F_{\alpha} (K, L-K) \]

- **If any calculated $T^2$ value exceeds $UCL_2$, we may conclude that, at the confidence level of (1-$\alpha$)%, the analyzed structure is in damaged state**
- **If a signal is normal, it will be added to the baseline**
Lamb Wave Propagation

- Analytical solutions under idealized boundary conditions
  - wave equations
    \[
    \begin{align*}
    \frac{\partial^2 \phi}{\partial x^2} + \frac{\partial^2 \phi}{\partial z^2} + k_1^2 \phi &= 0 \quad \text{(longitudinal)} \\
    \frac{\partial^2 \psi}{\partial x^2} + \frac{\partial^2 \psi}{\partial z^2} + k_t^2 \psi &= 0 \quad \text{(transverse)}
    \end{align*}
    \]
  - dispersive equations
    \[
    \tan \sqrt{1 - \xi^2} \frac{d}{d} + \left( \frac{4 \xi^2 \sqrt{1 - \xi^2} \sqrt{\xi^2 - \zeta^2}}{(2 \xi^2 - 1)^2} \right)^{+1} = 0
    \]
  - strain output
    \[
    \varepsilon_x(x, t) \big|_{z=d} = \frac{1}{\mu} \sum_{k_s} \sum_{k_i} \left\{ \frac{\pi k_s s \left( k_i^2 \right) \cosh(s d) \cosh(q d)}{\Delta s'} \left( Y_1 - Y_2 \right) e^{ikx} \right\} e^{-ik\Delta \omega} \Delta \omega \\
    + \frac{1}{\mu} \sum_{k_s} \sum_{k_i} \left\{ \frac{\pi k_s s \left( k_i^2 \right) \sinh(s d) \sinh(q d)}{\Delta a'} \left( Y_1 + Y_2 \right) e^{ikx} \right\} e^{-ik\Delta \omega} \Delta \omega
    \]
Dynamic Analysis

Healthy structure response study

Under 50 kHz excitation

Under 90 kHz excitation

Under 130 kHz excitation

Symmetric and Antisymmetric amplitudes versus frequency
Local Detection Demonstration

Damage is clearly detected in the $T^2$ chart!
Detection Sensitivity under Different Excitation Frequency

- Center frequency of the excitation signal
  \[ f(t) = \frac{1}{2} \sin(\omega_0 t)[1 - \cos\left(\frac{2\pi t}{T}\right)] \]

Detection results under different center frequencies

![Graph showing detection results under different center frequencies](image-url)
Detection sensitivity with respect to crack depth and width

Major factor to the detection sensitivity is the crack depth, when the crack width is small compared to the wavelength.
On-going Work

- Set up a laboratory test bed of wind turbine with coupled gearbox and rotating blades
- Data-driven local detection approach applied to gearbox vibration monitoring
- Develop *dynamic* and hybrid models of blade-gearbox system
- Develop dynamic interrogation strategy
Thanks

DDDAS will enable the autonomous diagnosis of wind turbines that operate under non-steady condition with variation/uncertainty