Turbine Condition Monitoring

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Outline

- ✓ Part I: Condition Monitoring Practice
- ✓ Part II: Reliability Theory
- ✓ Part III: Prediction of status patterns in wind turbines

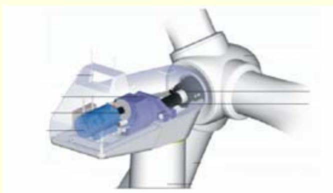
Part I: Why Condition Monitoring of Wind Turbines?

- ✓ Eliminate unscheduled maintenance activities
- ✓ Scheduled maintenance during low or no-wind periods
- ✓ Reduce the number of site visits for conditions assessment
- ✓ Reduce overtime expenses and production losses

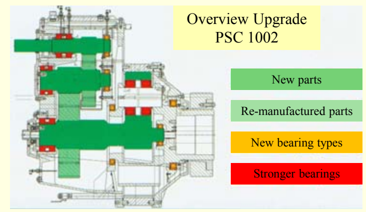
Practice: Why Condition Monitoring of Wind Turbines?

- ✓ Reduce failure rate of components and systems
- ✓ Reduce the inventory volume of components
- ✓ Reduce unscheduled equipment use, e.g., cranes
- ✓ Prevent secondary damage
- ✓ Extend component life-time
- ✓ Maximize profit

Damages to the Drive Train

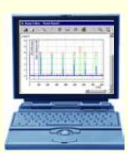


Retrofit Experience in Gear Technology



Nearly every manufacturer of wind turbine gears considers retrofit arrangements

Example: Solutions for Wind Turbine Monitoring



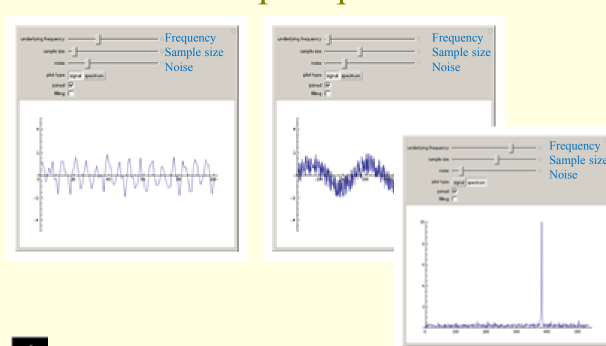
VIBSCANNER®
✓ 1-channel FFT data collector and analyzer

OMNITREND®
✓ PC software

VIBXPERT®
✓ 2-channel FFT data collector and machine analyzer

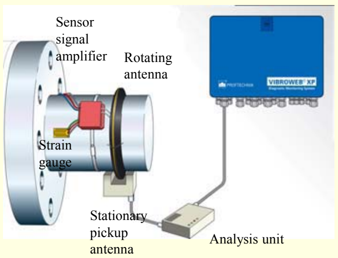
FFT = Fast Fourier Transform

Example Spectra



http://demonstrations.wolfram.com/FrequencySpectrumOfANoisySignal/

Torque Measurement

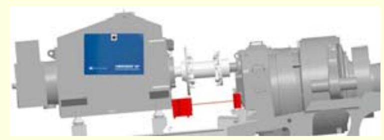


✓ Data analysis: Rain-flow method

Alignment Monitoring

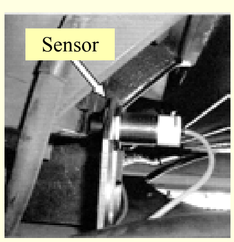
Monitoring of the alignment between the generator and the gearbox due to changing operating loads:

✓ Permanent or temporary
✓ Relative and absolute



Basic Measurements

Displacement
Inductive sensor - VIB 5.991-DIS



Basic Measurements

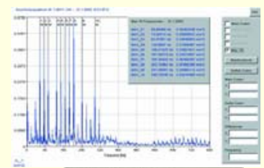
Number of revolutions per minute
Inductive sensor - VIB 5.992-BA

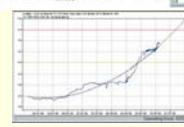
Basic Measurements

Acceleration
Power-LineDrive - Type - VIB 6.195
ICP-Type - VIB 6.172

Vibration Measurements

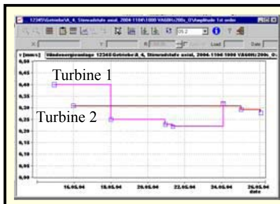
Example Parameters:
✓ Velocity (peak, RMS)
✓ Acceleration (peak, RMS)
✓ Displacement
✓ RPM
✓ Time waveform





RMS = root-mean-square
RPM= revolutions per minute

Amplitude Trending



Why narrow-band trending?
✓ Condition diagnosis for the specific machine component frequencies

Why differentiate operating states?
✓ Identification of 'critical' operating conditions

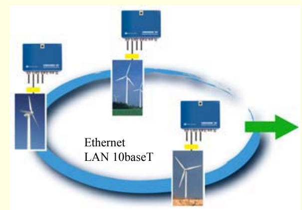
Alarm Level Adapts to the Operating State

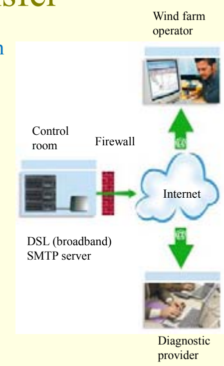
	Op. state 1	Op. state 2
Generator speed	500 - 1000 rpm	1001 - 1500 rpm
Wind velocity (0-20mA)	5 - 10 m/s	10.5 - 15 m/s
Generator power (0-20mA)	100 - 500 kW	501 kW - 2500 kW

Data Transfer

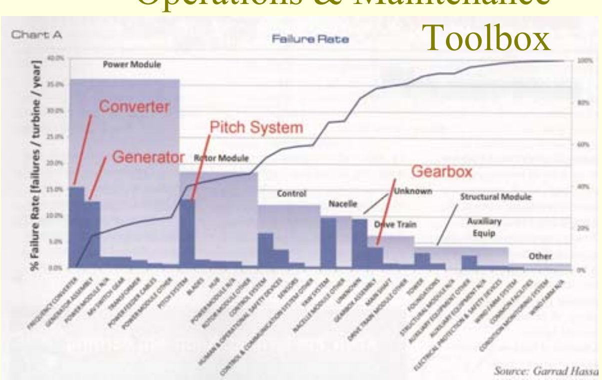
Data Transfer

Online System

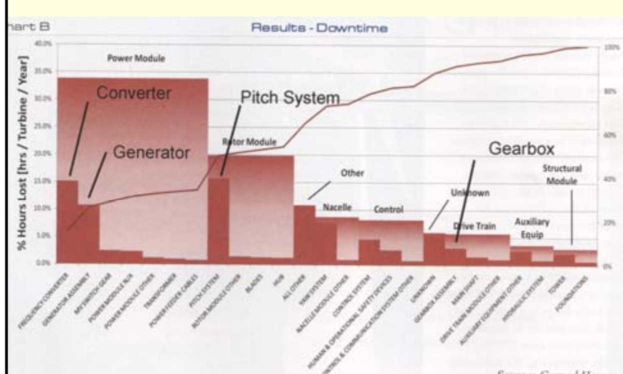




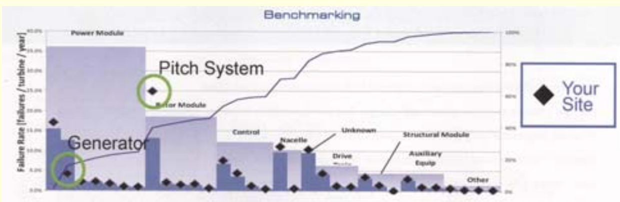
Operations & Maintenance Toolbox



O&M Toolbox



O&M Toolbox



Wind Today, Vol. 5, No. 1, 2010.

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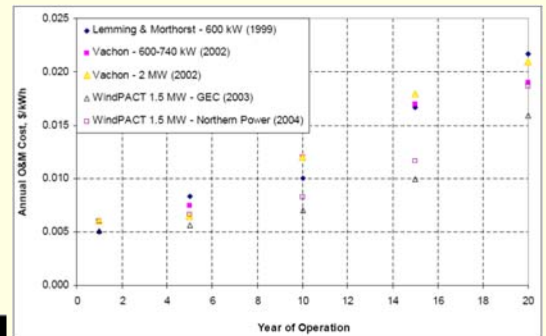
O & M Cost



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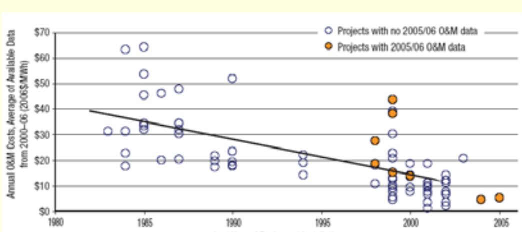
O & M Cost

Average O&M Cost Based on Data from 2000 - 2006 by Last Year of Equipment Installation



Source: Berkeley Lab database; five data points suppressed to protect confidentiality.

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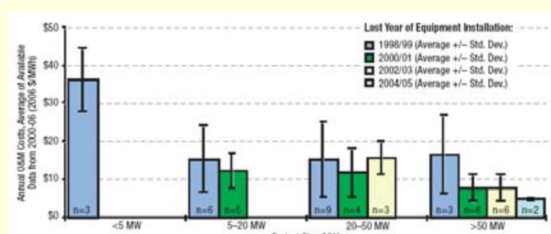
O & M Cost

Average O&M Cost Based on Data from 2000-2006 by Project Size



Source: Berkeley Lab database; averages shown only for groups of two or more projects.

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Part II: Reliability Theory

- ✓ Introduction
- ✓ Basic reliability models
- ✓ Fault detection

Reliability

Definition: Reliability is the **probability** that a component or system will perform a required function for a given period of time when used under **stated operating conditions**

Reliability: Basic Theory

Reliability function

$$R(t) = \Pr(T \geq t) \qquad T = \text{time to failure}$$

$R(t)$ = probability that the time to failure is greater than or equal t

$$F(t) = 1 - R(t)$$

$F(t)$ = probability that a failure occurs before time t

Probability Density Function

$F(t)$ = probability that a failure occurs before time t

$$\frac{dF(t)}{dt} = f(t) \qquad F(t) = \int_0^t f(t^{'})dt^{'}$$

$f(t)$ = failure probabilty density function

Reliability

$R(t)$ = probability that the time to failure is greater than or equal t

$$R(t) = \int_t^{\infty} f(t^{'})dt^{'}$$

Mean Time to Failure

$$MTTF = E(T) = \int_0^{\infty} t \times f(t)dt$$

$$MTTF = \int_0^{\infty} R(t)dt$$

Failure Rate Function

$$\lambda(t) = \frac{f(t)}{R(t)}$$

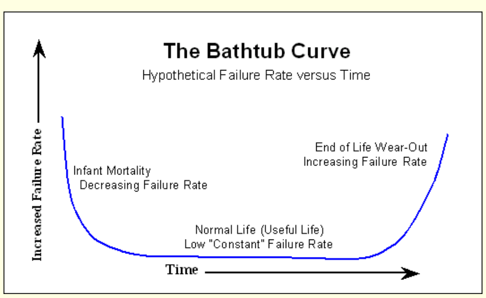
Recall

$$R(t) = \int_t^{\infty} f(t')dt'$$

$$R(t) = \exp\left[-\int_0^t \lambda(t')dt'\right]$$

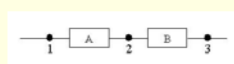
- ✓ Decreasing failure rate (DFR)
- ✓ Constant failure rate (CFR)
- ✓ Increasing failure rate (IFR)

Bathtub Curve



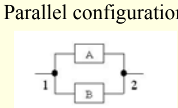
System Reliability

Serial configuration



$R_A(t) \times R_B(t)$

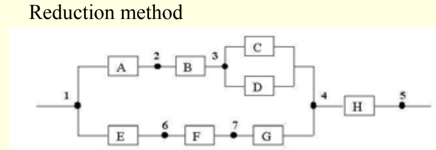
Parallel configuration



$1-(1-R_A(t))\times(1-R_B(t)) =$

$R_A(t) + R_B(t) - R_A(t)\times R_B(t)$

Reduction method



Maintainability

$$\Pr\{T \le t\} = H(t) = \int_0^t h(t')dt'$$

T = time to repair a failed unit

$$MTTR = \int_0^\infty t \times h(t)dt$$

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Fault Detection

- ✓Statistical methods, quality control
  - Single variable
  - Two variables
  - Clustering
- ✓Residual approach
  - Low bed temperature example
  - Wind turbine power curve example

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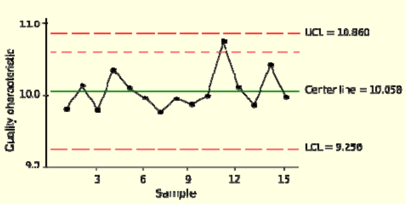
X Bar Chart for the Mean

$$\bar{x} = \frac{x_1 + x_2 + \ldots + x_n}{n} \qquad \bar{\bar{x}} = \frac{\bar{x}_1 + \bar{x}_2 + \ldots + \bar{x}_m}{m} \qquad \bar{R} = \frac{R_1 + R_2 + \ldots + R_m}{m}$$

$$R = \max\{x_1, x_2, \ldots, x_n\} - \min\{x_1, x_2, \ldots, x_n\}$$



$$UCL = \bar{\bar{x}} + A_2\bar{R}$$

$$CenterLine = \bar{\bar{x}}$$

$$LCL = \bar{\bar{x}} - A_2\bar{R}$$

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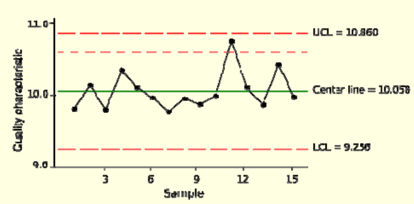
R Bar Chart for the Variation

$$UCL = D_4\bar{R}$$

$$CenterLine = \bar{R}$$

$$LCL = D_3\bar{R}$$

$$\bar{R} = \frac{R_1 + R_2 + \ldots + R_m}{m}$$



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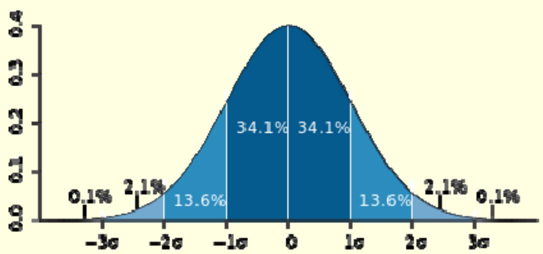
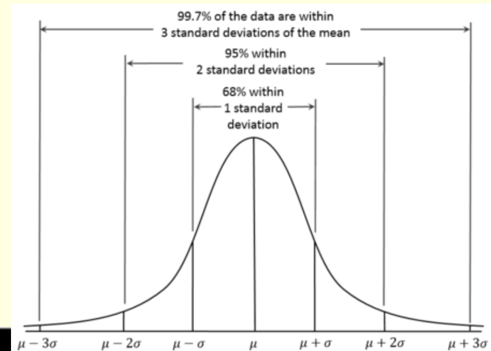
Six Sigma Concept

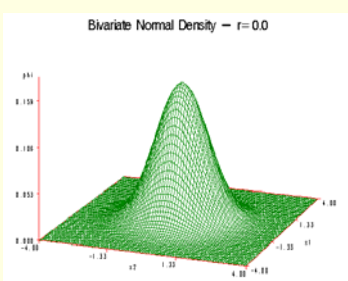


Six Sigma Concept

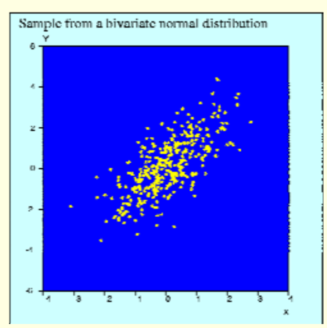


Two Variables

- ✓ Each variable seems to be normal
- ✓ Looking at them together generates faults



Joint Normal Regions



H^2 Chart

$$\overline{\mathbf{x}} = \frac{\mathbf{x}_1 + \mathbf{x}_2 + \ldots + \mathbf{x}_n}{n} \qquad \mathbf{S} = \frac{1}{n-1}\sum_{i=1}^{n}(\mathbf{x}_i - \overline{\mathbf{x}})(\mathbf{x}_i - \overline{\mathbf{x}})'$$

$$\chi_0^2 = \frac{n}{\sigma_1^2\sigma_2^2 - \sigma_{12}^2}\left[\sigma_2^2(\overline{x}_1 - \mu_1)^2 + \sigma_1^2(\overline{x}_2 - \mu_2)^2 - 2\sigma_{12}(\overline{x}_1 - \mu_1)(\overline{x}_2 - \mu_2)\right]$$

$\chi_{\alpha,2}^2$ Chi-square statistics

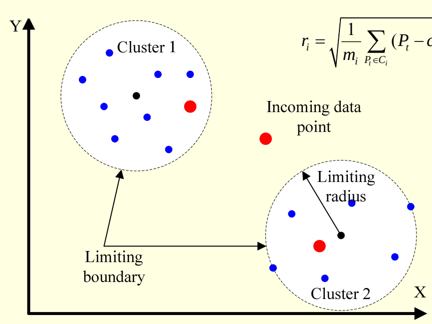
$\chi_0^2 > \chi_{\alpha,2}^2$ Not normal, out of control

Clustering

- ✓ Many variables
- ✓ Large data sets
- ✓ Data steams
- ✓ Normal distribution does not apply

Symbol	Description
C_i	The i^{th} cluster
c_i	The centroid of cluster C_i
K	The number of clusters
m_i	The number of points in C_i

2-Dimensional Example



Residual Approach

- ✓ No fixed mean
- ✓ No obvious patterns, e.g., clusters
- ✓ Underlying process model can be constructed
- ✓ Data mining, linear regression, principal component analysis

How to Obtain Residual?

$y = f_{real}(x)$ Actual process

$\hat{y} = f(x)$ Identified process model, e.g., data mining

Residual $\varepsilon = \hat{y} - y$

Predicted parameter

Observed parameter

Low Bed Temperature Example

- ✓A combustion process
- ✓A sensor is installed to measure the low bed temperature of a boiler
- ✓How to detect the sensor failures?

Low Bed Temperature Example

Process variables $\hat{y} = f_y(\boldsymbol{x}, \boldsymbol{v})$

Process variable	Description	Engineering unit
$x(1)$	Coal input	Scaled between 0-100
$x(2)$	Oat hull input	Scaled between 0-100
$x(3)$	Primary air input	Scaled between 0-100
$x(4)$	Secondary air input 1	Scaled between 0-100
$x(5)$	Secondary air input 2	Scaled between 0-100
$v(1)$	Coal quality	BTU/lb
$v(2)$	Oat hull quality	BTU/lb
$y(1)$	Lower bed temperature	°F

Model's Performance

$$\mu_{Train} = \frac{1}{g}\sum_{i=1}^{g}(y_{t_i} - \hat{y}_{t_i})$$ Mean training error

$$\sigma_{Train} = \sqrt{\frac{1}{g-1}\sum_{i=1}^{g}((y_{t_i} - \hat{y}_{t_i}) - \mu_{Train})^2}$$

Std of the training error

Sampling Test Data Points

$$\mu_{Test} = \frac{1}{n}\sum_{i=1}^{n}(y_{t_{g+i}} - \hat{y}_{t_{g+i}})$$ Mean test error

$$\sigma_{Test} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}((y_{t_{g+i}} - \hat{y}_{t_{g+i}}) - \mu_{Test})^2}$$

Std of the test error

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Control Limits

$$UCL_1 = \mu_{Train} + 3\frac{\sigma_{Train}}{\sqrt{n}}$$

$$CenterLine_1 = \mu_{Train}$$

$$LCL_1 = \mu_{Train} - 3\frac{\sigma_{Train}}{\sqrt{n}}$$

Monitor the mean test error

Test data - > Measured data

$$UCL_2 = \frac{\sigma^2_{Train}}{n-1} \times \chi^2_{\frac{\alpha}{2}, n-1}$$

$$CenterLine_2 = \sigma^2_{Train}$$

$$LCL_2 = 0$$

Monitor the test error's std

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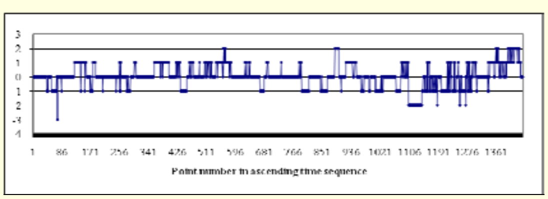
No Temperature Sensor Failures



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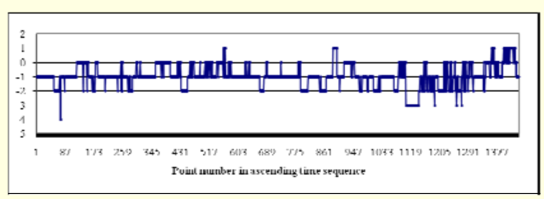
Bias Temperature Sensor Failures



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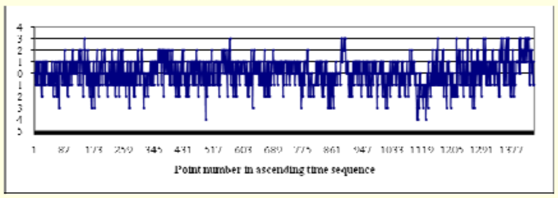
Variation Temperature Sensor Failures



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Wind Turbine Power Curve Monitoring

- ✓ Identify a power curve function based on normal training data points
- ✓ Compute the power curve model's performance in terms of the mean training error and std of the training error
- ✓ Construct control limits for monitoring mean test error and std of the test error

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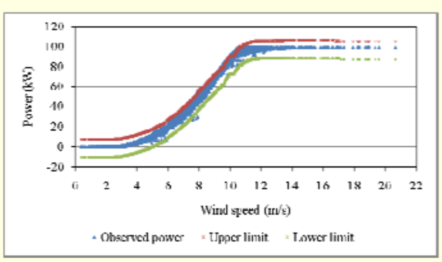
Power Curve Monitoring



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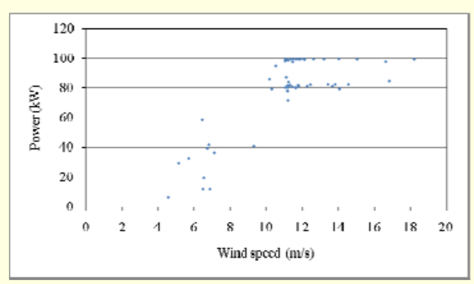
Identified Abnormalities



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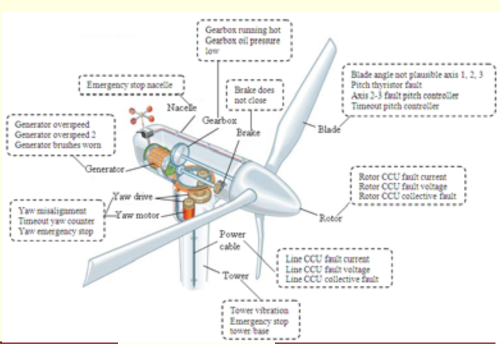
Part III: Prediction of status patterns in wind turbines

What is status code?

- ✓ Status code identifies various operating conditions or events during operations of a wind turbine
- ✓ Typical wind turbine may generate over 400 status codes
- ✓ Status categories

Category	Sample status	Severity
1	Generator overspeed, safety chain	High
2	Blade angle asymmetry, pitch thyristor fault	Medium
3	Turbine stopped due to calm	Low
4	Fault reset, system OK	None

Status codes vs. turbine components

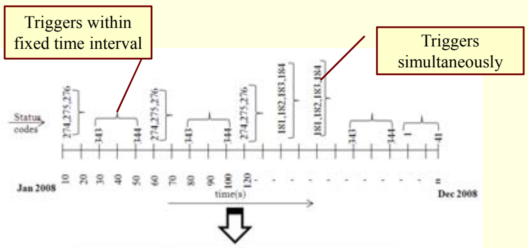


Why status pattern?

- ✓ Individual status codes may not be fault informative
- ✓ A typical status pattern may reflect fault in specific wind turbine component
- ✓ Useful in identification of *sympathetic* faults

– Blade angle asymmetry: *Actual fault*
  - Dirty slip rings: *Sympathetic fault*
– Yaw misalignment: *Actual fault*
  - Cable twisting: *Sympathetic fault*
– Emergency Stop: *Actual fault*
  - Collective control unit (CCU) fault: *Sympathetic fault*

Status pattern identification

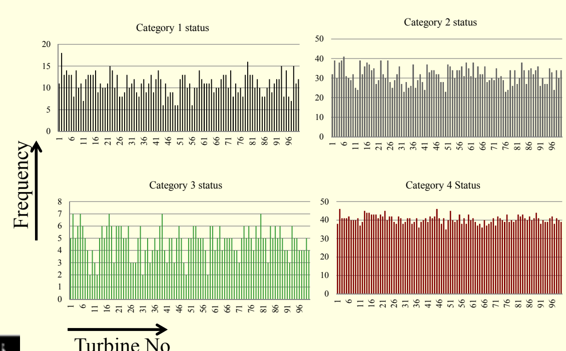


Status codes sequence	Frequent	Relevant	Status pattern
274,275,276	✓	✓	Yes
343,344	✓	✓	Yes
181,182,183,184	✓	✗	No
1,41	✗	✓	No

Case Study: Fault Identification

- One hundred 1.5 MW wind turbines
- One year of data (10 [min] interval), Jan 2008 - Dec 2008
- *Objective*
  - Identify critical status patterns in wind turbine
  - Predict status pattern well ahead of time
  - Develop a performance monitoring scheme

Status frequency of 100 turbines

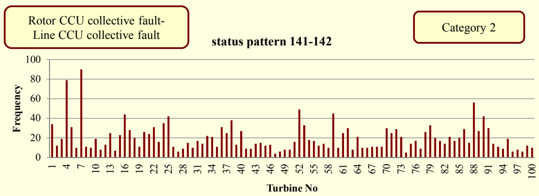


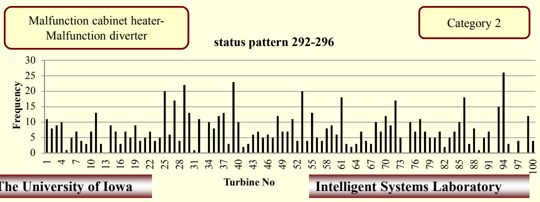
Identified status patterns

No.	Status pattern (category)	Description	Distribution statistics
1	141(1), 142(2)	Rotor CCU collective faults, Line CCU collective faults	Neg. binomial (n=2, p=0.10072)
2	45(2),52(2)	Hydraulic pump time too high, Gearbox oil pressure too low	Poisson (λ=1.09)
3	105(2),113(2)	Rotor CCU fault voltage, Line CCU fault voltage	Geometric (p=0.139)
4	63(1),118(1)	Safety chain, Emergency stop nacelle / hub	Poisson (λ=3.47)
5	292(3),296(3)	Malfunction Cabinet Heaters, Malfunction Diverter	Geometric (p=0.118)
6	106(2),114(2)	Rotor CCU fault current, Line CCU fault current	Neg. binomial (n=4,p=0.442)
7	343(2),344(1)	Blade angle not plausible axis 3,Pitch malfunction 2 or 3 blades	Geometric (p=0.066)
8	296(3),285(3)	Malfunction Diverter, Timeout CAN communication to hub	Poison(λ=0.5)
9	122(2),296(3)	Collective fault pitch controller, Malfunction Diverter	Poisson(λ=1.23)
10	122(2),285(3)	Collective fault pitch controller, Timeout CAN communication to hub	Poisson(λ=0.28)
11	274(1),275(1),276(1)	Pitch thyristor 1 fault, Pitch thyristor 2 fault, Pitch thyristor 3 fault	Geometric (p=0.0658)
12	223(2),342(2),343(2)	Blade angle not plausible axis 1,Blade angle not plausible axis 2,Blade angle not plausible axis 3	Geometric (p=0.067)
13	212(1),213(1),214(1)	Battery voltage not OK axis 1,Battery voltage not OK axis 2,Battery voltage not OK axis 3	Poisson (λ=0.9)
14	141(2),142(2),208(2)	Rotor CCU collective faults, Line CCU collective faults, No activity CAN-Bus CCU	Poisson (λ=1.46)
15	106(2),114(2),141(2),142(2)	Rotor CCU fault current, Line CCU fault current, Rotor CCU collective faults, Line CCU collective faults	Poisson (λ=1.23)
16	106(2),114(2),141(2),142(2), 208(2)	Rotor CCU fault current, Line CCU fault current, Rotor CCU collective faults, Line CCU collective faults, No activity CAN-Bus CCU	Poisson (λ=1.23)

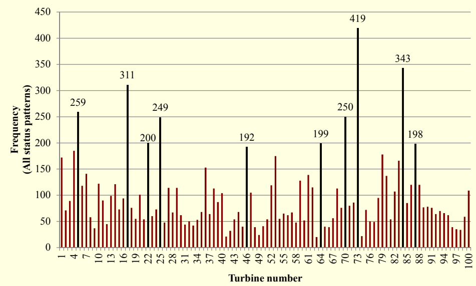
Status patterns based on category 2 statuses are the most common among 100 turbines

Status pattern distribution





Fault prone turbines



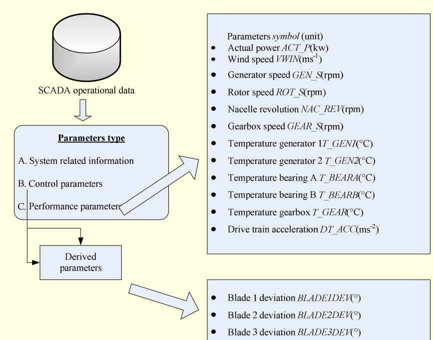
Turbines 005,017,022,025,046,064,070,073,084,087 are affected by frequent patterns

Association among statuses

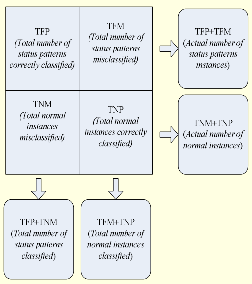
– Criteria used
  - *Frequency of status pattern in a year* (Min. η=10)
  - *Strength of a status pattern* (Min. Str.=0.8)

Turbine 73						
No.	**Str. %**	**Condition (a)**	**Prediction (c)**	**η(a)**	**η(c)**	**η(aUc)**
1	100	Pitch thyristor 1 fault, Pitch thyristor 2 fault=>	Pitch thyristor 3 fault	298	298	298
2	100	Pitch thyristor 2 fault=>	Pitch thyristor 1 fault	298	298	298
3	100	Pitch thyristor 3 fault=>	Pitch thyristor 2 fault	298	298	298
4	100	Line CCU collective faults=>	Turbine stopped due to calm	41	41	41
5	100	Emergency stop nacelle / hub=>	Line CCU fault voltage	28	28	28
6	100	Blade angle not plausible axis 1, Blade angle not plausible axis 3=>	Blade angle not plausible axis 2	25	25	25
7	100	Pitch malfunction 2 or 3 blades=>	Blade angle not plausible axis 3	22	47	22
8	100	Emergency stop nacelle / hub, Line CCU collective faults, Line CCU fault voltage=>	Turbine stopped due to calm	13	41	13
9	100	Line CCU collective faults, Line CCU fault voltage=>	Turbine stopped due to calm	13	41	13

Fault Prognosis



Criteria for prediction



$$\text{Accuracy} = \frac{\text{TFP} + \text{TNP}}{\text{TFP} + \text{TFM} + \text{TNM} + \text{TNP}}$$

$$\text{Senstivity} = \frac{\text{TFP}}{\text{TFP+TFM}}$$

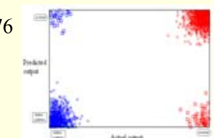
$$\text{Specificity} = \frac{\text{TNP}}{\text{TNM} + \text{TNP}}$$

Status pattern prediction

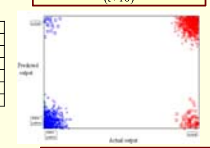
Prediction of status pattern 274=>275=>276

Pitch thyristor 1 fault=>Pitch thyristor 2 fault=> Pitch thyristor 3 fault

Time stamp	Accuracy (%)	Sensitivity (%)	Specificity (%)
t+10	95.67	96.8	94.7
t+20	95.37	97.1	94.0
t+30	94.88	96.8	93.4
t+40	94.19	96.3	92.4
t+50	96.08	97.4	95.1
t+60	93.77	95.0	92.9



Actual and predicted output (t+10)



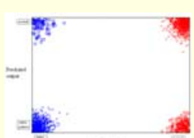
Actual and predicted output (t+60)

Status pattern prediction

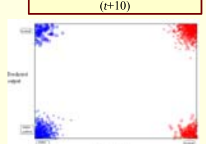
Prediction of status pattern 343=>344

Blade angle not plausible axis 3=>Pitch malfunction 2 or 3 blades

Time stamp	Accuracy (%)	Sensitivity (%)	Specificity (%)
t+10	86.12	88.2	84.2
t+20	86.26	89.8	83.3
t+30	85.20	90.1	81.0
t+40	85.47	86.1	85.0
t+50	85.53	88.6	82.8
t+60	84.64	85.4	84.1



Actual and predicted output (t+10)



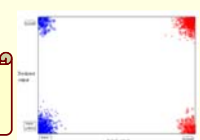
Actual and predicted output (t+60)

Status pattern prediction

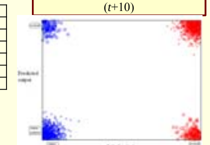
Prediction of status pattern 223=>342=>343

Blade angle not plausible axis 1=> Blade angle not plausible axis 2=> Blade angle not plausible axis 3

Time stamp	Accuracy (%)	Sensitivity (%)	Specificity (%)
t+10	86.75	88.4	85.3
t+20	87.59	90.5	85.1
t+30	86.57	90.6	83.1
t+40	84.36	87.8	81.4
t+50	86.98	89.2	85.1
t+60	84.64	87.8	85.7



Actual and predicted output (t+10)



Actual and predicted output (t+60)

Conclusion

- ✓ The Supervisory Control And Data Acquisition (SCADA) System installed at each wind turbine contains information about errors encountered by the system which is useful for performance monitoring
- ✓ Data mining is a useful tool for wind turbine fault prognosis