Turbine Reliability, Maintenance and Fault Detection

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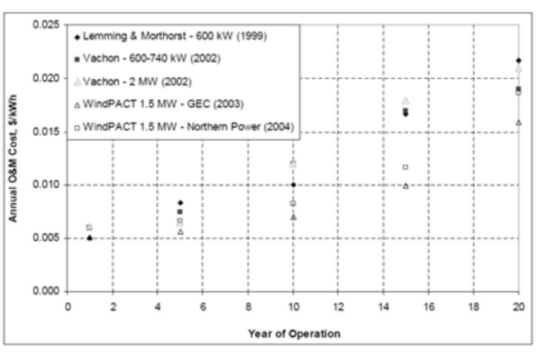
Outline

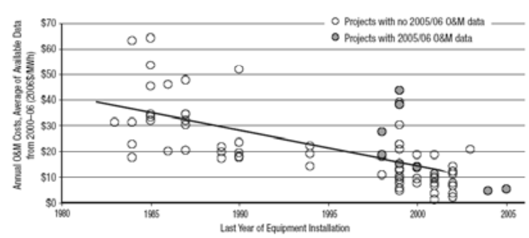
- Introduction
- Basic reliability models
- Fault detection

O & M Cost



O & M Cost

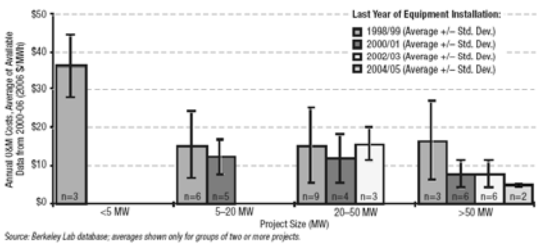
- Average O&M Costs for Available Data Years from 2000-2006, by Last Year of Equipment



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

O & M Cost

- Average O&M Costs for Available Data Years from 2000-2006, by Project Size



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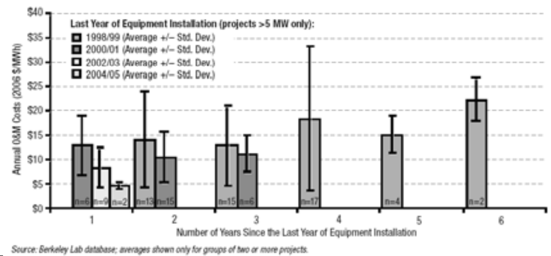
O & M Cost

- Annual Average O&M Costs, by Project Age and Last Year of Equipment Installation



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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**

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Reliability, Some Theories

- Reliability function

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

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

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

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

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Probability Density Function

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

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

Mean Time to Failure

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

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

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Failure Rate Function

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

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

1. Increasing failure rate (IFR)
2. Decreasing failure rate (DFR)
3. Constant failure rate (CFR)

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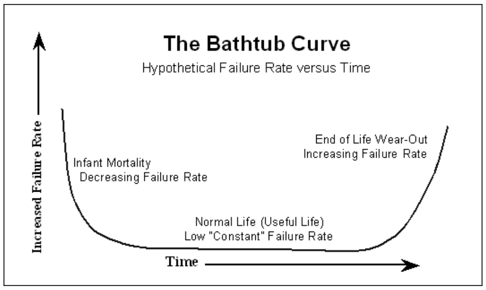
Bathtub Curve



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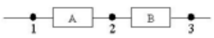
Reliability of Systems

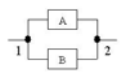
Serial configuration

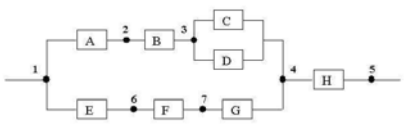


$R_A(t) \times R_B(t)$

Parallel configuration

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





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Maintainability

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

T, time to repaire a failed unit

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

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Reducing Maintenance Cost

- Develop logistics plan
- Identify opportunities for redundancy
- Improve training
- Improve maintainability
- Implement condition monitoring

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Some Recommendations

- Quantify O&M costs over time
- Develop component reliability
- Identify high-risk components and understand failure modes
- Re-evaluate design standards

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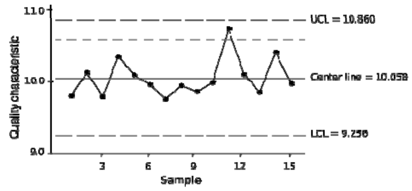
Fault Detection

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

X Bar Chart for the Mean

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

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



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

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

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

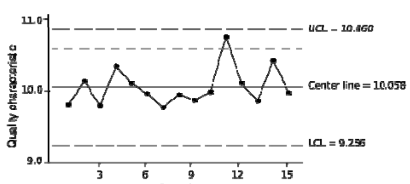
R Bar Chart for the Variation

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

$$CenterLine = \bar{R}$$

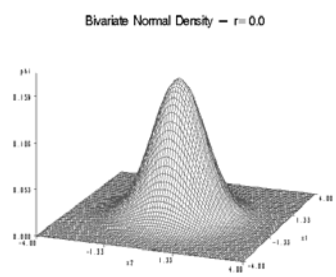
$$LCL = D_3\bar{R}$$

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



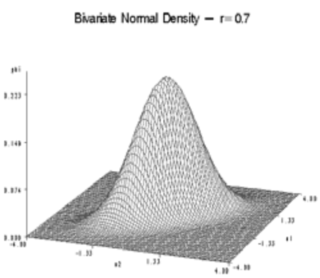
Two Variables

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

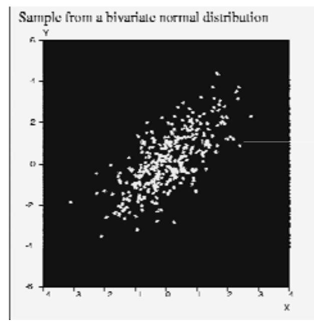


Two Variables with Correlation

- How to monitor two variables if they have correlation



Joint Normal Regions



H^2 Chart

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

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

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

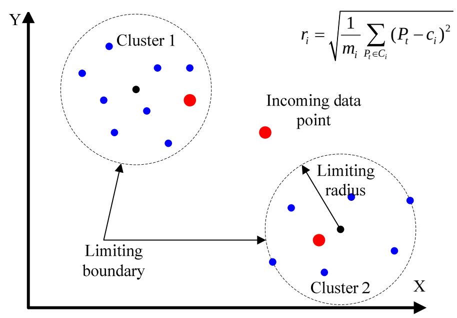
$\chi_0^2 > \chi^2_{\alpha,2}$ Not normal, out of control

Clustering

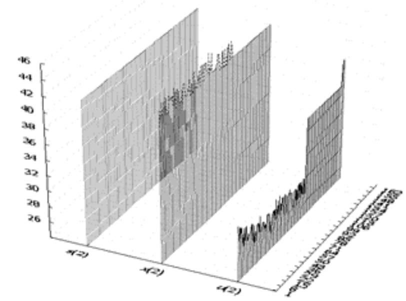
- Too many variables
- Large data set
- Data steams
- No normal distributions

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-Dimension Example



3-Dimension Example



Residual Approach

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

How to Get Residual

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

$$\hat{y} = f(x)$$ ← Identified process model

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

Predicted (→ $\hat{y}$), Observed (→ y)

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

What is the 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

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

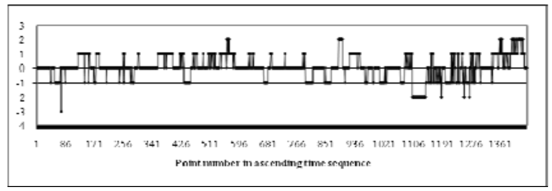
$$UCL_2 = \frac{\sigma^2_{Train}}{n-1} \times \chi^2_{\frac{\alpha}{2},n-1}$$

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

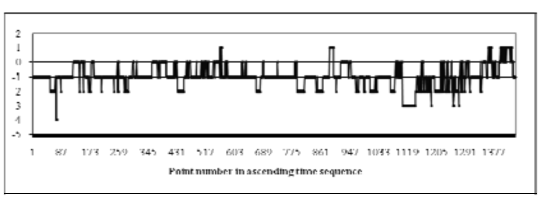
$$LCL_2 = 0$$

Monitor the test error's std

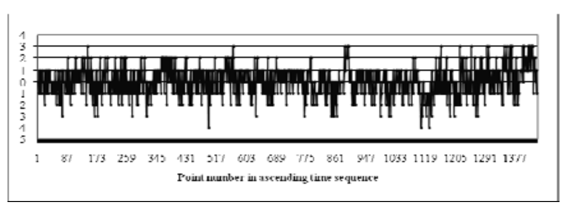
No Temperature Sensor Failures



Bias Temperature Sensor Failures



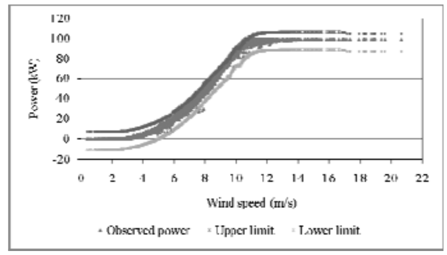
Variation Temperature Sensor Failures



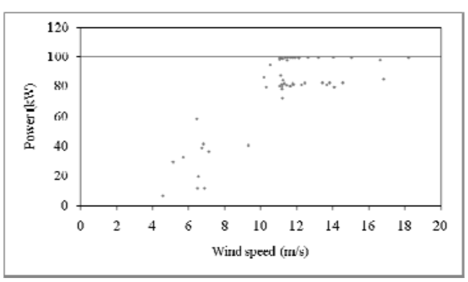
Wind Turbine Power Curve Monitoring

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

Power Curve Monitoring



Identified Abnormalities



Power Curve Profile Monitoring

- Use parametric models to identify a power curve, then **monitor the parameters**

$$y = f(x, \boldsymbol{\theta}) = a\frac{1+me^{-x/\tau}}{1+ne^{-x/\tau}}$$ Nonlinear

$$f(v) = \begin{cases} 0, v < v_{cut\_in} \\ \lambda v + \eta, v_{cut-in} \le v \le v_{rated} \\ P_{rated}, v > v_{rated} \end{cases}$$ Linear

Linear Scenario

$$f(v)=\begin{cases}0, v < v_{cut\_in}\\ \lambda v+\eta, v_{cut-in} \le v \le v_{rated}\\ P_{rated}, v > v_{rated}\end{cases}$$

$$(\lambda, \eta)$$

Monitor this two parameters by using T^2 chart?

Summary

- Reliability models
  - Collect failure
  - Estimate pdf
  - Design logistic plans
- Fault detection
  - Single variable
  - Multiple variables