


Wind Turbine Prognostic Health Management: Field-Failure Predictions Based on Failure-Time Data with Dynamic Covariate Information

Time: 10:00-10:45
Location: DTU Compute/CITIES
Building 303B: Room 026

Presented by: Michael S. Czahor on 24 August 2015

Presenter Profile

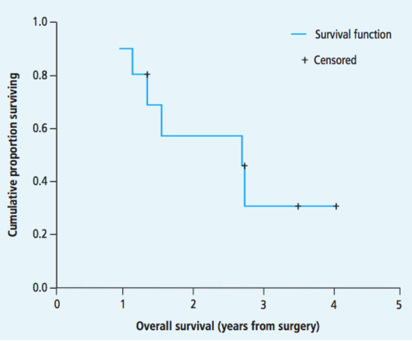
Michael S. Czahor

- Co-Major PhD Fellowship Student
- Employed by National Science Foundation/Iowa State University WESEP Dept.
- IGERT Student (Integrative Graduate Education and Research Traineeship)
- WESEP (Wind Energy Science Engineering Policy) and Statistics Co-Major
- Rowan University 2013 (Bachelors in Mathematics)
- Comcast Spectacor Statistician 2012-2013
- Fraunhofer IWES Statistician Summer 2015
- Major Professor: Dr. William Meeker

Presenter Profile

Received his Bachelors in mathematics from Rowan University in May 2013. During his time at Rowan he focused heavily on statistical methods and theory. He is currently an IGERT Fellow pursuing a co-major PhD in Wind Energy Science Engineering Policy and Statistics. During his senior year at Rowan, Michael interned as a junior level statistician with Comcast Spectacor in Philadelphia. His research at ISU is focused on modern systems (wind turbines) that are providing large amounts of system-use and environmental data .While using this data, with appropriate statistical modeling; he hopes to provide improved predictions of component and system lifetimes. The benefits from this research will include, but not be limited to providing important prognostic information on maintenance and replacement needs for individual units.

Recent Research Topics

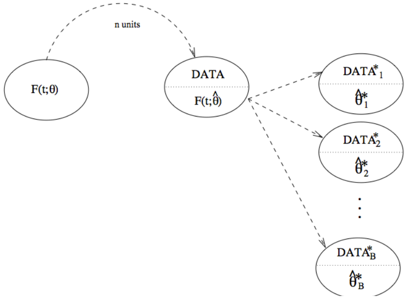


Cox Proportional Hazard Modeling for Cancer patients (Spring 13)

- No past information matters
- Survival Analysis Techniques
- Non parametric Kaplan Meir Estimation

Bootstrap with fractional weights (Dirichlet Distribution) (Fall 13)

- Simulation techniques via R statistical coding algorithms
- Smoothing of median distributions

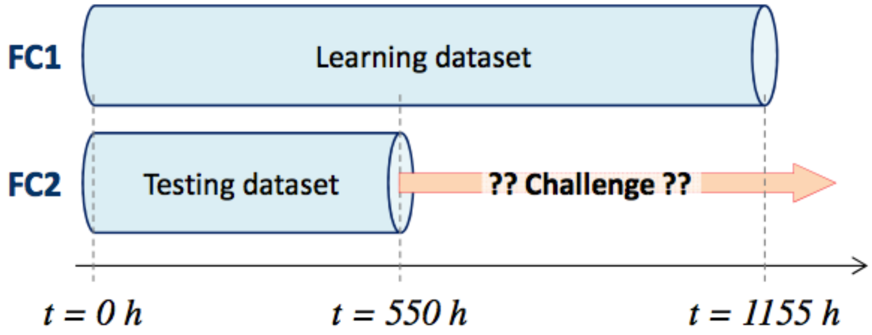


Proton Exchange Membrane Fuel Cell RUL (Summer 2014/Current)

- Enhance prediction accuracy
- Cross validation algorithms
- Sample size issue
- Improve industry/university approaches

Power Converter Failure Predictive via Dynamic Covariate utilization in a Cumulative Damage Model (Fall 2014/Current)

- Prognostic health management of wind turbines
- Minimize crane costs via predictive maintenance
- Big Data sorting algorithms



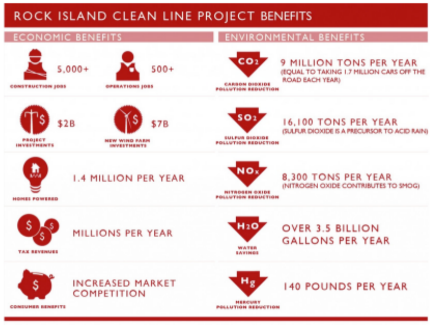
Recent Publications

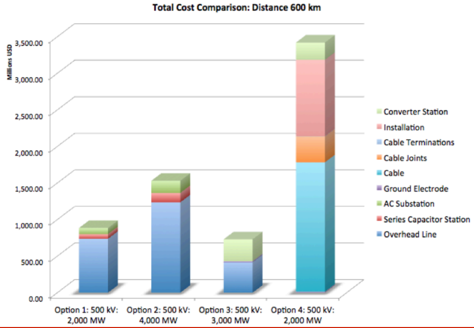
American Institute of Mathematical Sciences Energy Journal

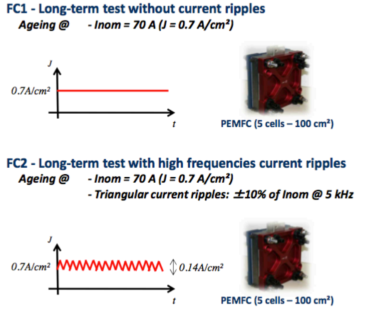
- **Armando L. Figueroa-Acevedo, Michael S. Czahor and David E. Jahn (2015) A comparison of the technological, economic, public policy, and environmental factors of HVDC and HVAC interregional transmission. *AIMS Energy* 3(1): 144-161 (Published)**

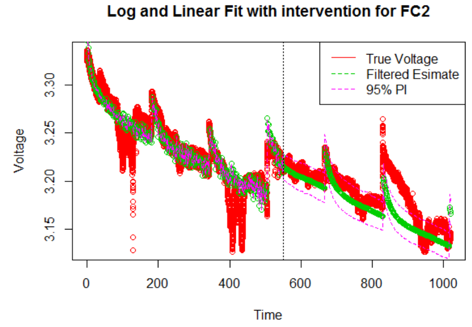
International Journal of Prognostics and Health Management

- **Qianqian Shan, Michael S. Czahor and Dr. William Q. Meeker (2015) Proton electrolyte membrane fuel cell prognostics using non-linear Bayesian tracking methods and intervention analysis. *IJPHM (Editing)***









Presentation Outline

PART 1

- **ISU Degree Program in Wind Energy Science Engineering and Policy (WESEP)**
- **Wind-Related Research Activities**
- **Wind Energy Student Organization at Iowa State University**

PART 2

- **My Research at Iowa State:**
  largely based on work with Dr. William Q. Meeker[1]
- **Conclusions/Questions and Answers**

Part 1: WESEP at ISU

Wind Energy Science, Engineering & Policy

- A PhD degree in WESEP (just like EE, ME, etc.)
- Interdepartmental → Participating Departments include

Aerospace Eng.	Sociology
Geological & Atmospheric Sciences	Economics
Agronomy	Statistics
Electrical & Computer Eng.	Journalism & Communications
Materials Science Eng.	Civil, Con & Environmental Eng.
Industrial & Man Systems Eng.	Mechanical Eng.

Research structure is by following thrusts:

I. Wind resource characterization & aerodynamics of wind farms
II. Wind energy conversion system and grid operations
III. Manufacturing, construction, and supply chain
IV. Turbine reliability & health monitoring
V. Economics, policy and public perception

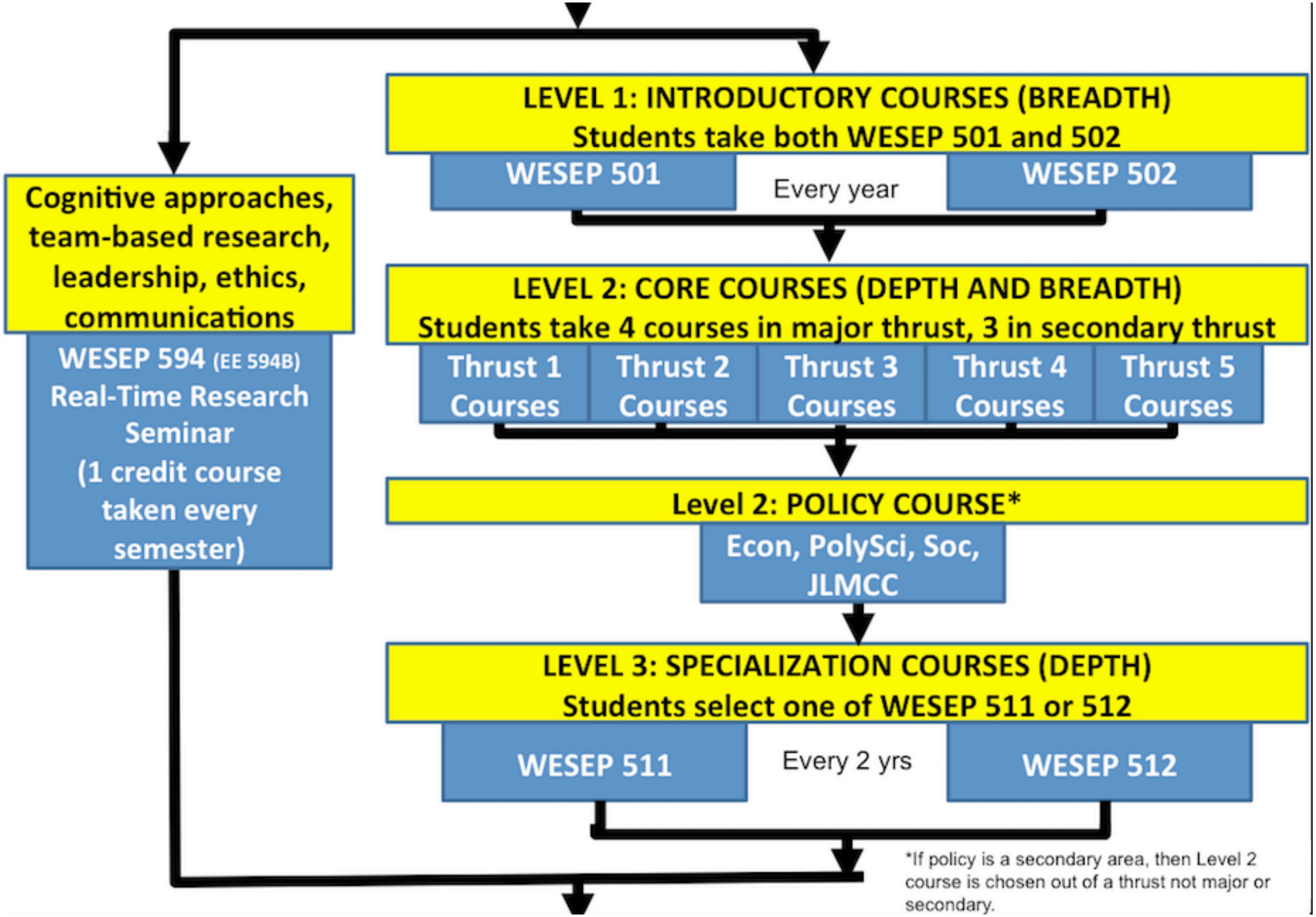
Dr. James D. McCalley
Principal Investigator

Wind Energy Science, Engineering & Policy

- Can enter PhD program wit either BS or BS/MS

- US WESEP students receive
  - For 24 to 30 months, $30,000/yr+ paid tuition and fees (via NSF)
  - Remaining time, $21,000/yr +paid tuition and fees
  - 3 months paid "international experience"
  - 3 months industry internship opportunity
  - Highly interdisciplinary training including:
    - WESEP 501: Wind Energy Resources
    - WESEP 502: Wind Energy Systems
    - WESEP 511: Wind Energy System Design
    - WESEP 512: Wind Energy System Deployment
    - WESEP 594: Wind Energy Research Seminar
    - "Core Courses"
      - 4 Primary area core courses
      - 3 Secondary area core courses
      - 1 Policy course

Overview of curriculum



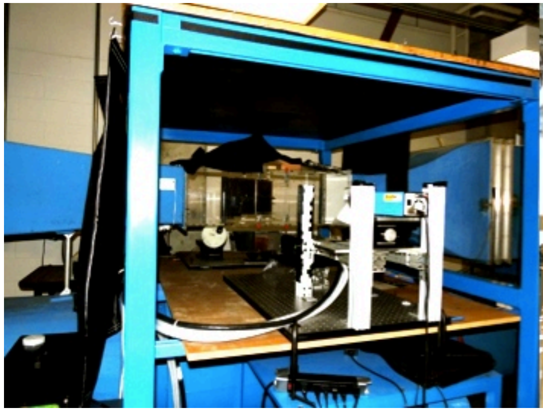
WESEP Students

Nick (EE/Econ) Michael (STAT) Austin (CE) Armando (EE) Matt (AeroE) Austin (ME) David (Met)

Helena (EE) Morteza (AeroE) Patrick (EE) Aaron (AeroE) Heather (ESM) Mat (CprE) Huiyi (IMSE)

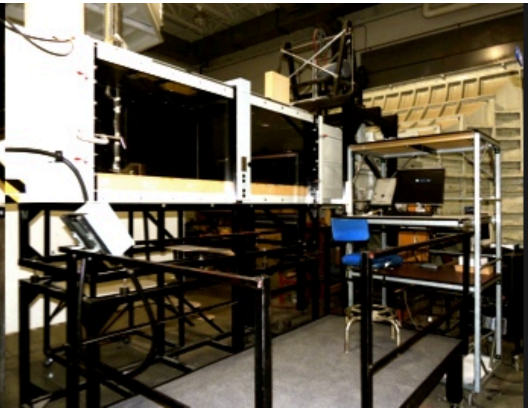
Arne (STAT) Bin (CE) Babar (EE) Robert (CE)

Wind simulation & Testing Lab



Blue Tunnel 180 mph

Laminar Flow Tunnel 90 mph



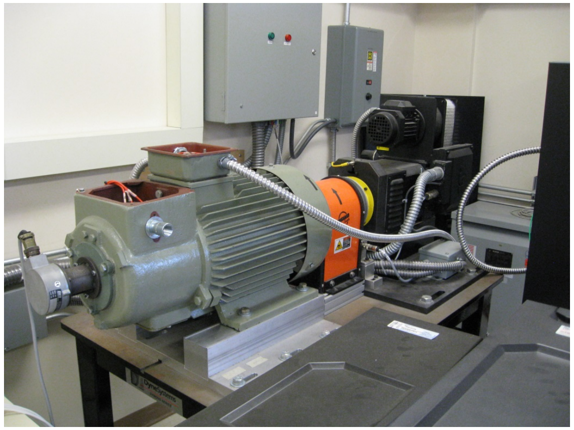
Bill James Tunnel 180 mph

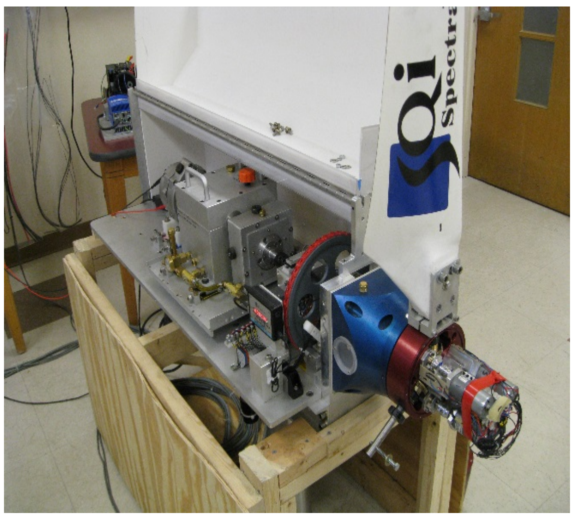
ABL 110 mph

Tornado Micro-burst Simulator

Icing Tunnel 200 mph and -30C

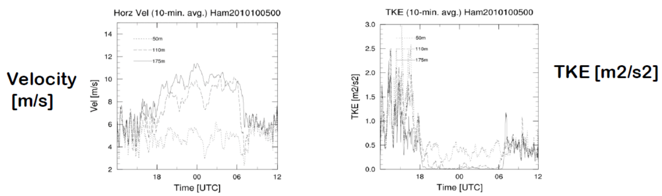
Wind Energy Systems Lab



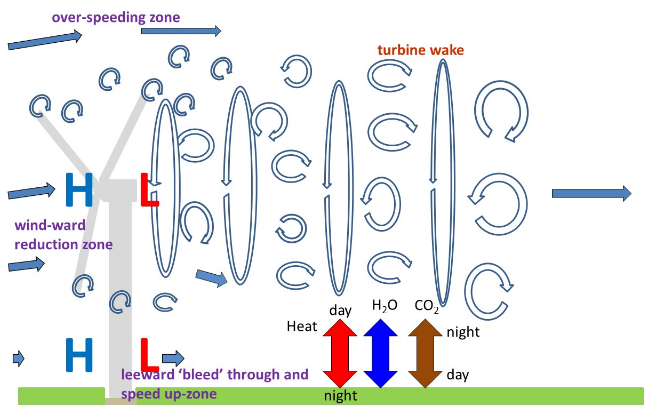


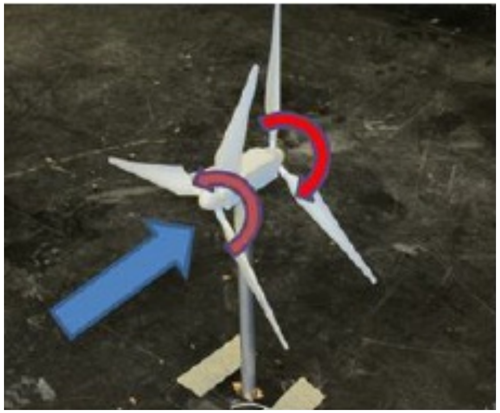
Nick David: Lab Coordinator

Wind-related research activities



$$\underbrace{\frac{\partial(TKE)}{\partial t}}_{\text{Time-tendency}} = \underbrace{-\frac{\partial}{\partial z}\left(\overline{w(TKE)^{1/2}}\right)}_{\text{TKE vert. flux}} + \underbrace{-\overline{uw}\frac{\partial U}{\partial z}}_{\text{Shear}} + \underbrace{\frac{g}{\Theta_o}\overline{w\theta}}_{\text{Buoyancy}} + \underbrace{-\frac{1}{B_1}\frac{(TKE)^{3/2}}{L}}_{\text{Dissipation}}$$





Using WRF for Short Term Wind Ramp Prediction---Wind Farms & Agricultural Yield --------------Dual Rotor Design----------

Takle/Gallus Meteorology ***Takle Agronomy*** ***Hu AeroE***

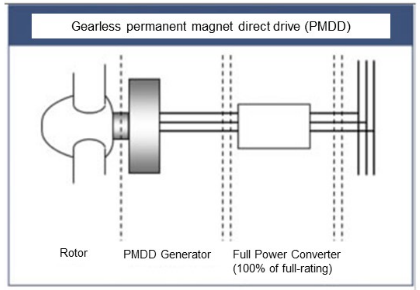


Fig. 5: Drive train configuration with DFIG. Source: http://www.goldwindamerica.com/technology-capabilities/pmdd/

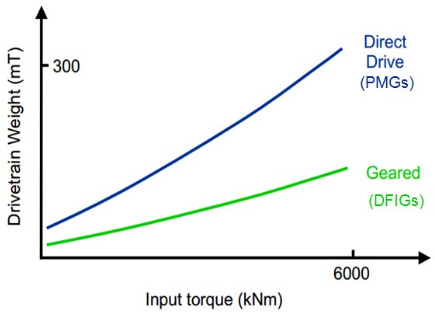
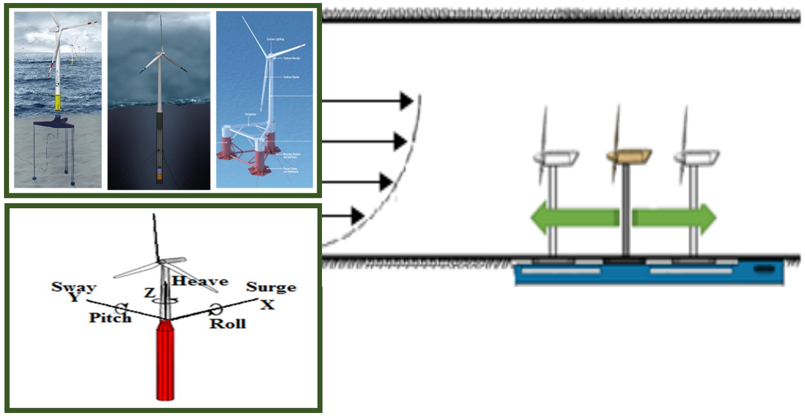


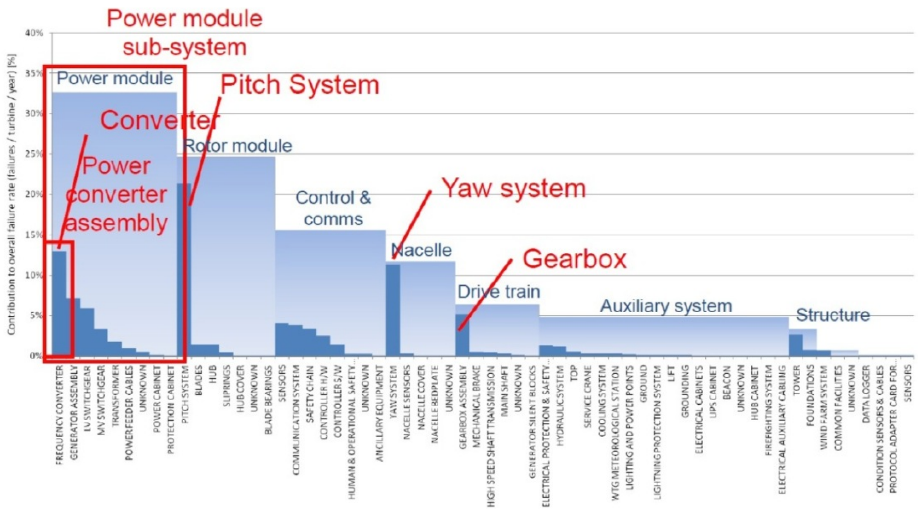
Fig. 6: Scaling of drivetrain weight due to input torque in wind turbines [12].



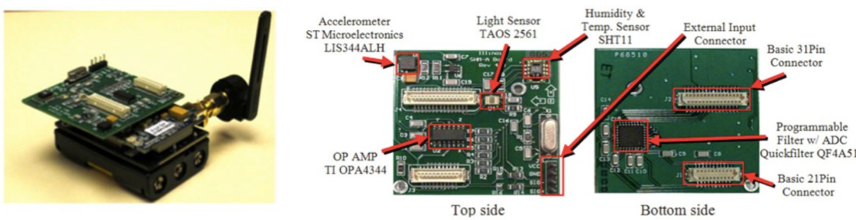
----------------Compact Permanent Magnet Generators---------------------------------Floating Offshore Wind Turbine Design-----------

Jiles EE/MatSci ***Hu AeroE***

Wind-related research activities

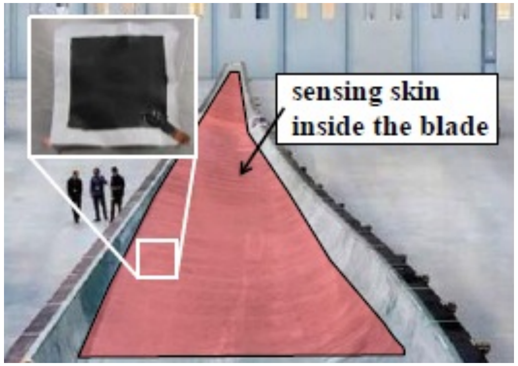


- Network of small, self-contained computers with wireless transceivers (nodes)
- Multihop communications
- Energy-constrained!

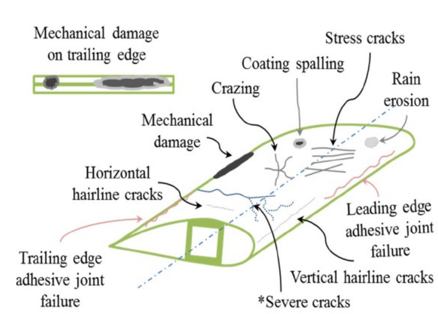


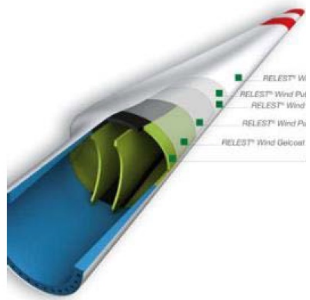
----------Reliability Assessment of Wind Turbine Components --Wireless Sensor Networks for Turbine Health Monitoring-

Meeker Statistics ***Qiao ECpE & Ceylan CE***



- Types of blade damage

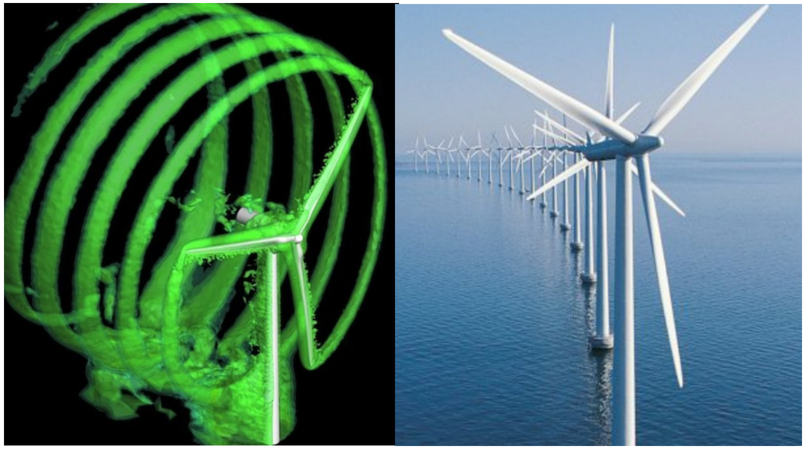


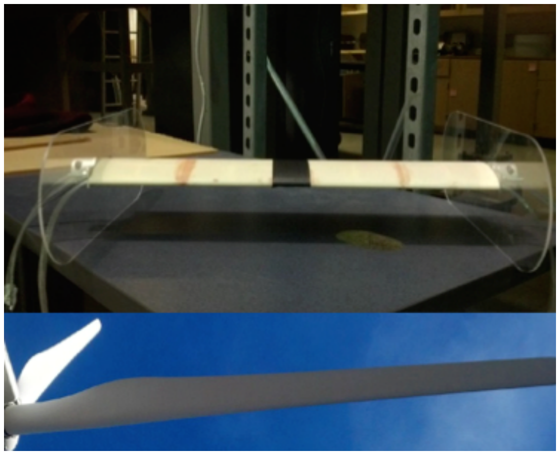


Dynamic Characterization of a Soft Elastomeric Capacitor-------Reducing Uncertainty WT Blade Health Inspection-------

LaFlamme CE ***Jackman IE***

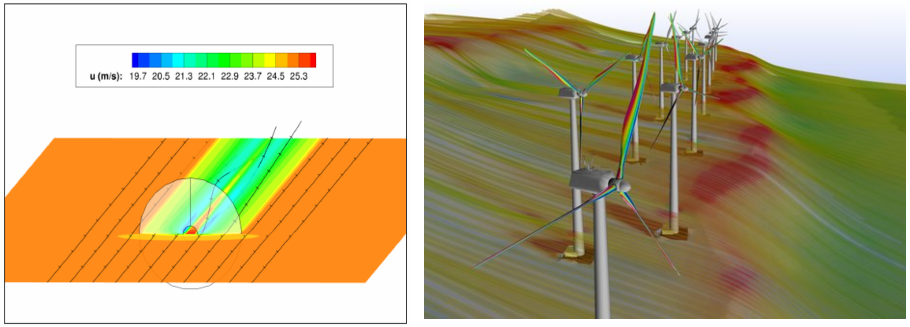
Wind-related research activities



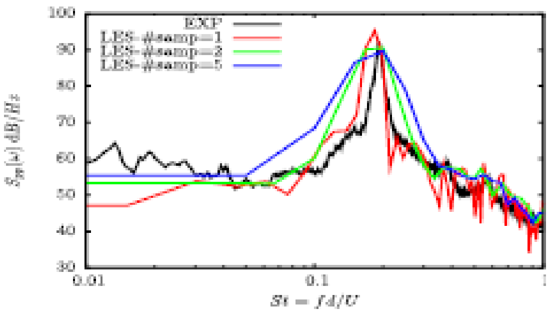


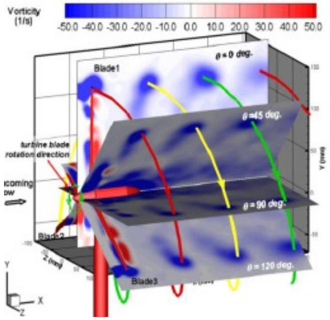
------Computational Fluid Structure Interaction Analysis------------------------Aeroelastic Loads & Response of WT Blades---

Hsu ME ***Sarkar AeroE***



Wind Speed =25 m/s





----------------------------CFD & WT Simulation----------------------------Wind Farm Aeroacoustics Modeling------Wake Interference----

Rajagopalan AeroE ***Sharma AeroE*** ***Hui AeroE***

Wind Energy Student Organization

Aaron Rosenberg
Research Collaboration Committee Director

Heather Sauder
Treasurer

Michael S. Czahor
Outreach Committee Director

Helena Khazdozian
President

Wind Energy Student Organization

“The Wind Energy Student Organization (WESO) promotes wind energy education and collaborative research at both the university and K-12 level. WESO is open to undergraduate, graduate, and professional students. General meetings are held monthly, which include a lecture on the topic of wind energy.

Dr. Eugene Takle
Mentor for WESO

WESO

Concluding Remarks (Part 1)

- National Science Funded IGERT WESEP Program → An interdisciplinary approach
- Wind Energy Research Taxonomies → Detailed research broken into 5 thrust areas
  - Thrust 1 → Wind Resource Characterization & Aerodynamics of Wind Farms
  - Thrust 2 → Wind Energy Conversion System and Grid Operations
  - Thrust 3 →Manufacturing, Construction, and Supply Chain
  - Thrust 4 → Turbine Reliability & Health Monitoring
  - Thrust 5 → Economics, Policy, and Public Perception
- On campus resources at Iowa State University
- WESO

Contact Information for this presentation

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Iowa State University
Co-Major: Wind Engineering/Statistics
Concentration: Reliability/Prognostics

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Part 2: My Research

Major Technological Changes in Reliability Practice

- Computationally-intensive models can be used to accurately predict some kinds of failure mechanisms (e.g., FEM is commonly used to predict growth of fatigue cracks in complicated geometries given known stress fields).

- Modern reliability field data including State/Operating/Environmental (SOE) information

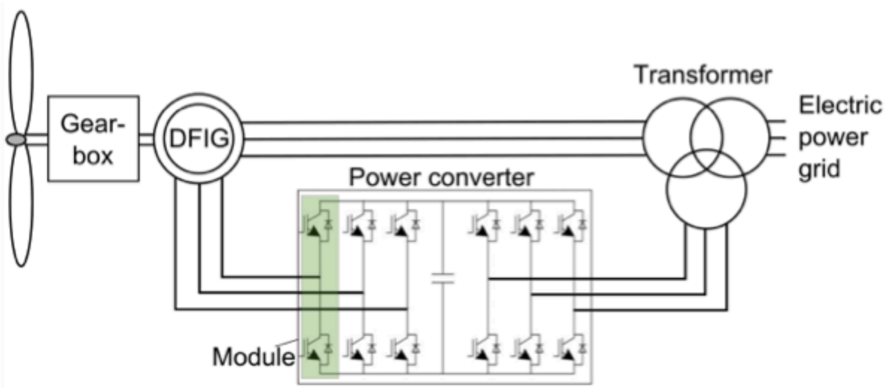
Modern Reliability Field Data

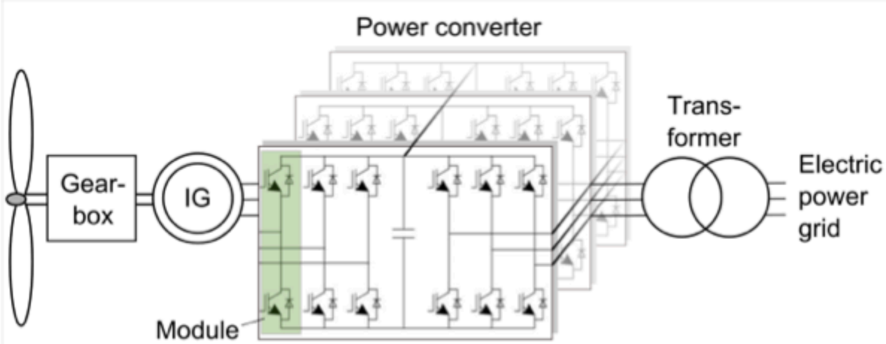
- Sensors, smart chips, as well as wired and wireless networks have changed data collection processes in many areas of commerce, engineering, and science.
- Products and systems are being designed to contain automatic data-collecting devices to track system state, operating environment and use/abuse information.
- System state, usage and environmental information dynamically recorded and/or transmitted back to manufacturers over the network (or downloaded periodically).
- Common structure: Potentially a large vector of dynamic covariate values is obtained periodically (e.g., a vector time series received every 10 minutes).

The next generation of field reliability data will contain richer information for prediction and other purposes.

Examples of Data

Wind Turbine Types

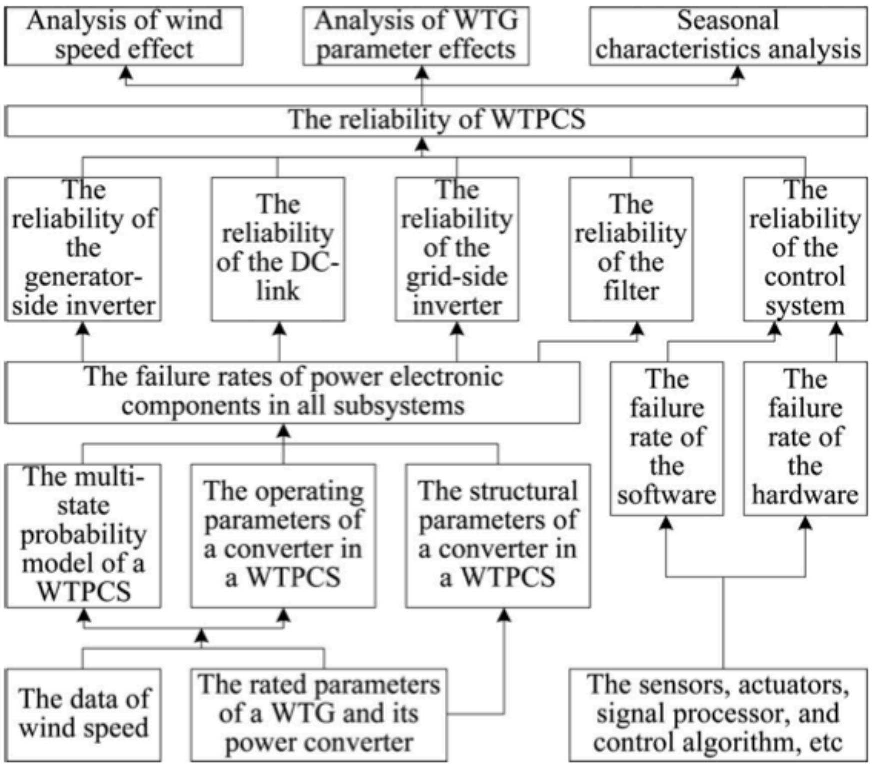


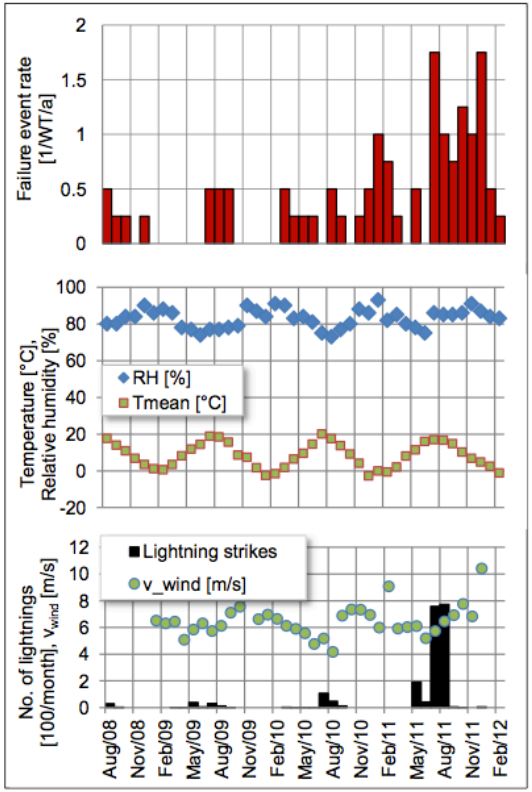


	Wind turbine type WT1	Wind turbine type WT2
Drivetrain	Geared, distributed	
Generator	DFIG	Squirrel-cage IG
Converter location	Inside nacelle	Tower bottom
Converter rating	Partially rated	Fully rated
Converter technology	IGBT based, low-voltage, back-to-back VSC	
Number of power modules	6 (grid-side converter: 3, generator-side conv.:3)	18 (grid-side conv.: 3x3, gen.-side conv.: 3x3)
Power module details	Water-cooled design without baseplate, integrated gate driver board, identical manufacturer	

Turbine Type Descriptions [7]

Examples of Data





Kaigui Xie (Left)

"Effect of Wind Speed on Wind Turbine Power Converter Reliability"

Dr-Ing. K. Fischer (Right)

Field-Experience Based Root-Cause Analysis of Power-Converter Failure in Wind Turbines [7]

Other Examples Providing System State/Operating/Environmental (SOE) data

- Locomotive engines
- Aircraft engines and structures
- Automobiles
- Power distribution transformers
- CT scanners and other large medical systems
- Wind turbines
- Solar energy power inverters
- Farm implements and large construction equipment, high-end printers/copiers, high-end computers, some home entertainment systems, and even smart phones

Applications of SOE Data

- Early warning of emerging reliability issues
- Prediction of retirements/replacements in a fleet of systems
- Prediction of warranty returns
- System health management (SHM), condition-based maintenance (CBM), prognostics
- Prediction of remaining life of individual systems

Meaning of SHM

System		Monitoring
	Health	
Structural		Management
	State	
Materials		Awareness
Engine		
Power system		
Prognostic		
etc.		

What is the Remaining Useful Life (RUL) of the system?
What is the Distribution of Remaining Life (DRL) of the system?

SHM, Condition-Based Maintenance and Prognostics (Short-Term Prediction of System Failure)

- The most common application of SOE data today
- Much literature including several journals and annual conferences devoted to SHM and prognostics
- Many sub applications

- Process monitoring and signal-detection algorithms can be used to detect unsafe operating conditions or precursors to system failure
- Condition-based maintenance (CBM) plan maintenance actions based on need instead of less efficient time-based schedules.
- Short-term predictions about the DRL of a system.

Prediction of Remaining Life of Individual Systems

- Need to estimate the distribution of **remaining life** for a ***single*** unit i, conditional on survival to the present time (i.e., age $t_{c\,i}$).

$$G(t) = \Pr(T_i \le t | \text{age } t_{c\,i}) = \frac{F_i(t_{c\,i} + t) - F_i(t_{c\,i})}{1 - F_i(t_{c\,i})}, \qquad t > 0.$$

- Allows one to compute a prediction interval for remaining life. Simple approximate method: quantiles estimates of the distribution $G(t)$.
- Little predictive ability without covariate information (see Hong, Meeker, and McCalley 2009 for an example)
- SOE data providing information on such variables as system load, temperature, and shock histories will allow more precise (narrower) prediction intervals.

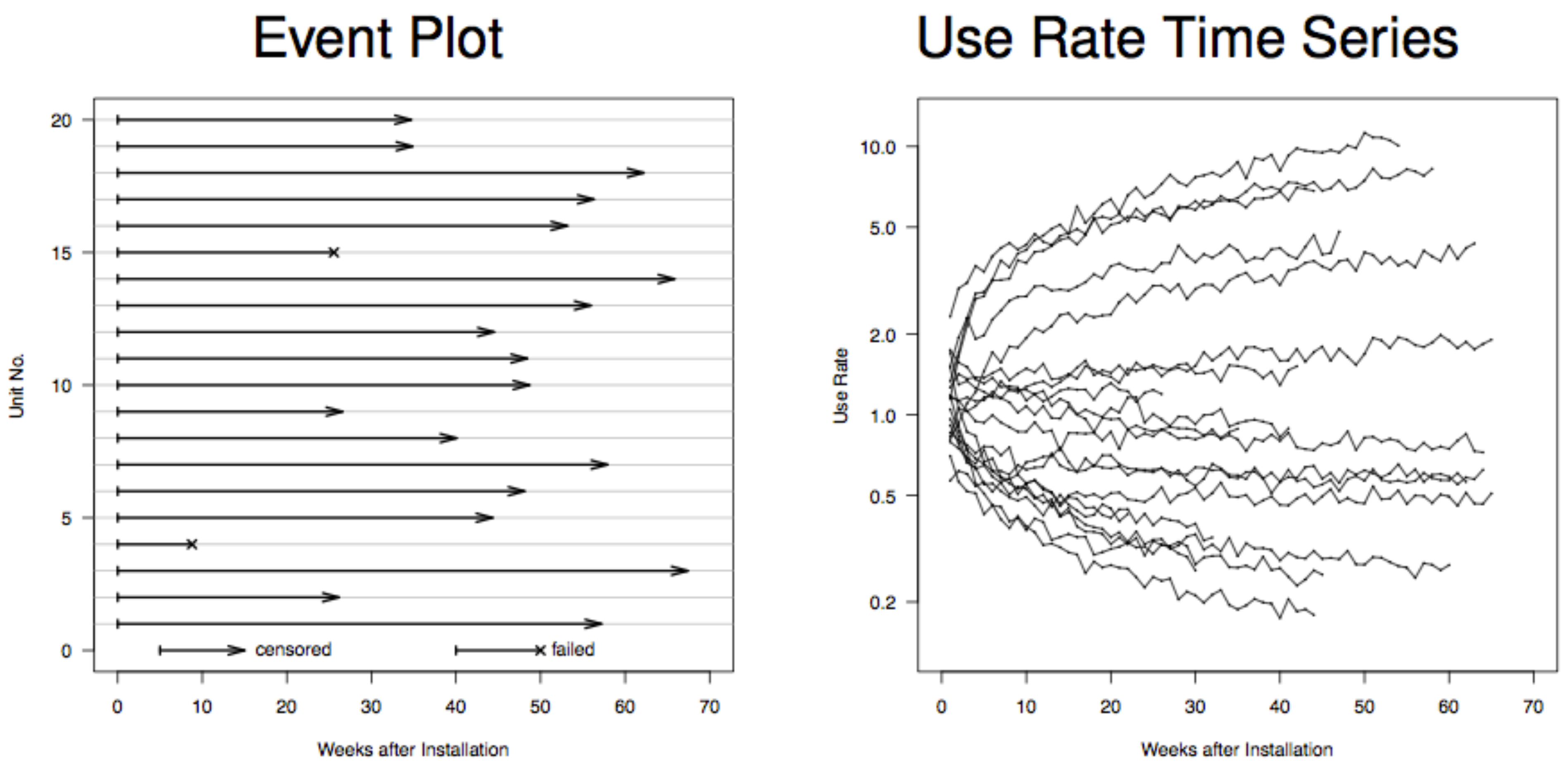
Example: Field-Failure Predictions Based on Failure-time Data with Dynamic Covariate Information

Outline

- Product D2 application
- Model for failure-time data with dynamic covariates
- Model for the dynamic covariates
- Field-failure prediction
- Improvement for using dynamic data

Goal: To develop general models for predicting the remaining life based on failure-time data with dynamic covariate information

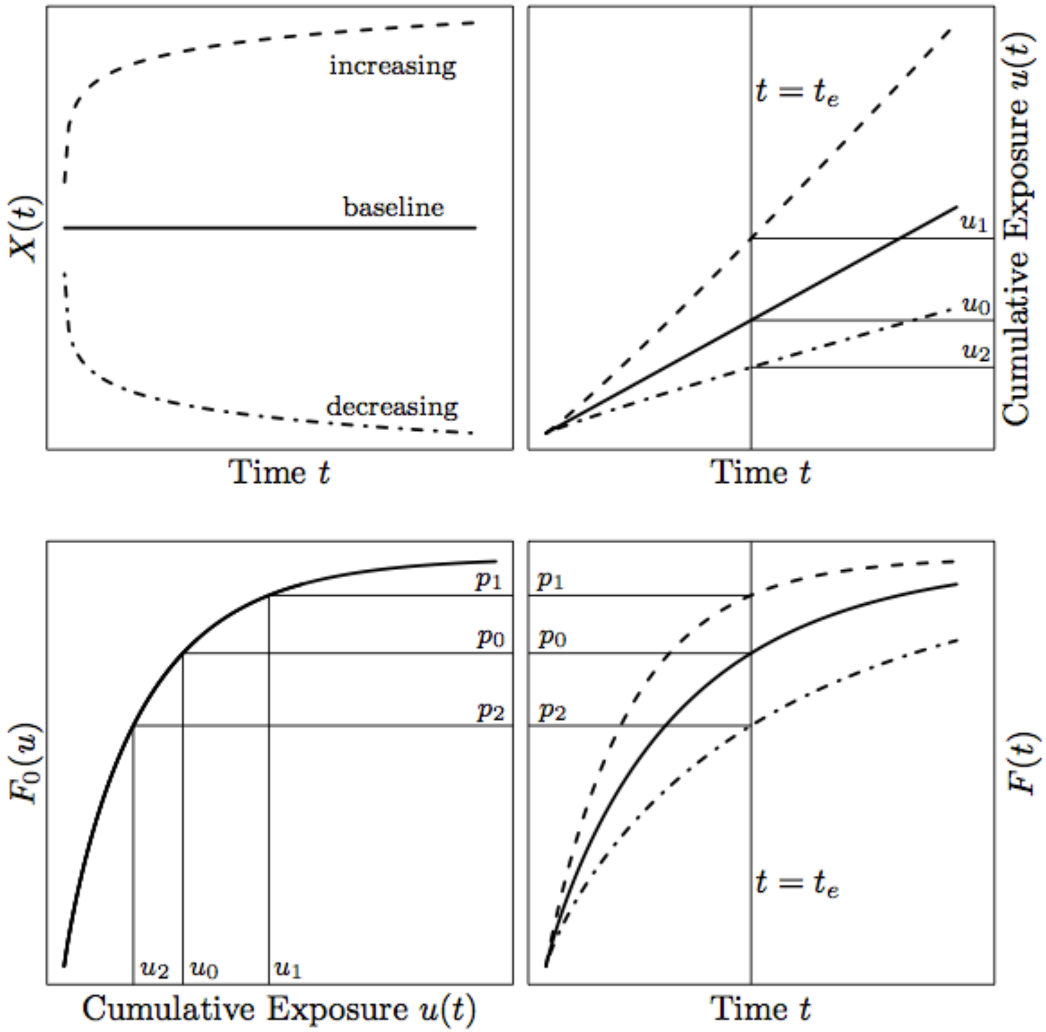
Product D2 Subset of Data (Ignoring Covariate Information)



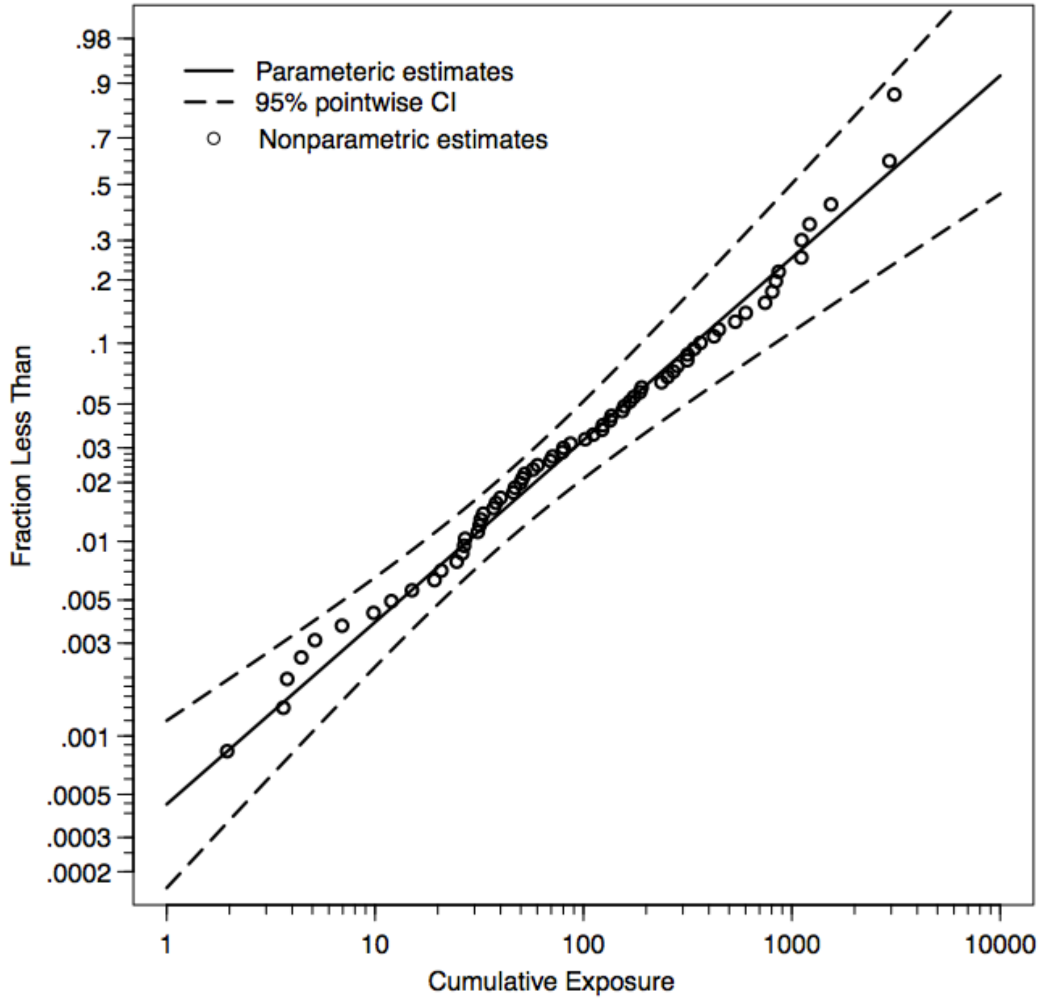
Cumulative Exposure/Damage (Sedyakin) Model

- Describes the effect of a dynamic (time-varying) covariate on failure-time.
- Covariate history $\boldsymbol{X}(\infty) = \boldsymbol{x}(\infty)$.
- Each unit accumulates **damage** $u(t) = u[t; \beta, \mathbf{x}(t)] = \int_0^t \exp[\beta x(s)]ds$.
- Each unit has cumulative damage random **threshold** U.
- Unit fails at time T when the amount of cumulative damage reaches U.
- The relationship between cumulative damage U and failure time T is $U = u(T) = \int_0^T \exp[\beta x(s)]ds$.
- The cumulative damage threshold U has **baseline** cdf $F_0(u, \theta_0)$.

Illustration of Cumulative Exposure/Damage Model



ML Estimate of the Cumulative Damage cdf



Model for the Covariate Process $X(t)$

Linear random effects model

$$X_i(t_{ij}) = \eta + Z_i(t_{ij})\boldsymbol{w}_i + \varepsilon_{ij}$$

where η is the mean, $Z_i(t_{ij}) = [1,\ \log(t_{ij})]$,
$\boldsymbol{w}_i = (w_{0i}, w_{1i})' \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{w}})$, $\varepsilon_{ij} \sim \mathrm{N}(0, \sigma^2)$.

For unit i, the random effect w_{0i} models the unit-to-unit variability at **time origins**

The random effect w_{1i} models the unit-to-unit variability in **trend**.

ε_{ij} models **within** unit variability at time t_{ij}.

Model for the Multivariate Covariate Process

- To predict a path into the future, it is necessary to have a parametric model that can adequately predict the covariate process
- In general, the following structure can be used $X(t) = m(t; \boldsymbol{\eta}) + a(t)$ with a mean structure and error term structure
- For example, temperature can be modeled as $X(t) = \text{Trend}(t) + \text{Seasonal}(t) + a(t)$
- For most applications, the vector autoregressive (VAR) model can be used

Distribution of Remaining Life

DRL for the surviving units provides basis for predictions of future field failures.

DRL for unit i is the distribution of T_i, given the current time in service t_i and covariate process history $\boldsymbol{X}_i(t_i) = \boldsymbol{x}_i(t_i)$.

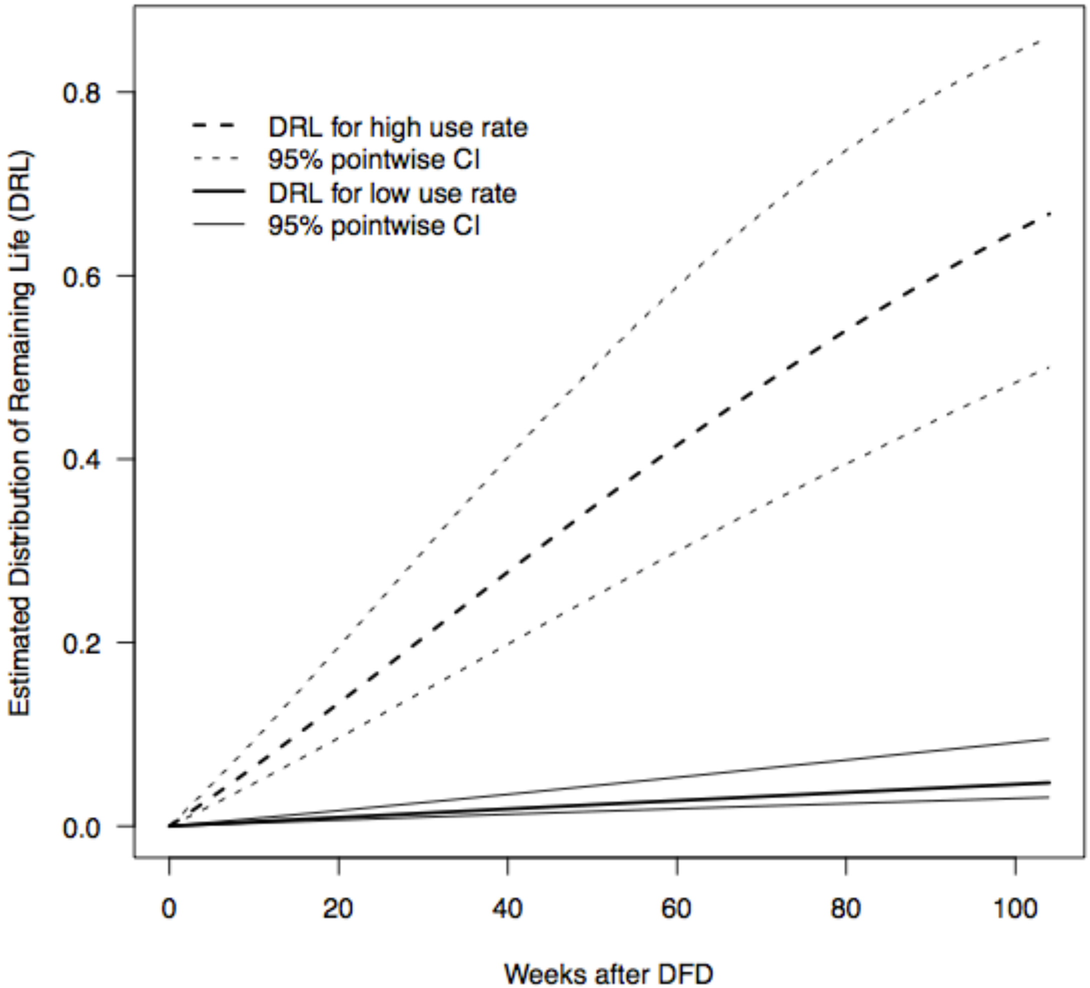
That is $\rho_i(s; \boldsymbol{\theta}) = \Pr[t_i < T_i \le t_i + s | T_i > t_i, \boldsymbol{X}_i(t_i)], \quad s > 0.$

In particular,

$$\begin{aligned}\rho_i(s; \boldsymbol{\theta}) &= \mathbf{E}_{\boldsymbol{X}_i(t_i, t_i+s)|\boldsymbol{X}_i(t_i)=\boldsymbol{x}_i(t_i)} \left\{\Pr[t_i < T_i \le t_i + s | T_i > t_i, \boldsymbol{X}_i(t_i), \boldsymbol{X}_i(t_i, t_i + s)]\right\} \\ &= \frac{\mathbf{E}_{\boldsymbol{X}_i(t_i, t_i+s)|\boldsymbol{X}_i(t_i)=\boldsymbol{x}_i(t_i)} \left\{F_0\left(u[t_i + s; \beta, \boldsymbol{X}_i(t_i + s)]; \boldsymbol{\theta}_0\right)\right\} - F_0\left(u[t_i; \beta, \boldsymbol{x}_i(t_i)]; \boldsymbol{\theta}_0\right)}{1 - F_0\left(u[t_i; \beta, \boldsymbol{x}_i(t_i)]; \boldsymbol{\theta}_0\right)}\end{aligned}$$

where $\boldsymbol{X}_i(t_1, t_2) = \{X_i(s) : t_1 < s \le t_2\}$ is the covariate history for unit i from time t_1 to time t_2.

Estimated DRL for Two Representative Units



Example: Outdoor Weathering Prediction

The degradation of organic paints and coatings is primarily driven by UV exposure with temperature and humidity as secondary factors.

Data collected to study of service life of an organic coatings in an outdoor environment

Outdoor weathering experiments were carried out in Gaithersburg, MD, between 2002 and 2006

Groups of 36 specimens placed in a covered outdoor environmental chamber on the roof of a building on the NIST campus, starting at different times of the year

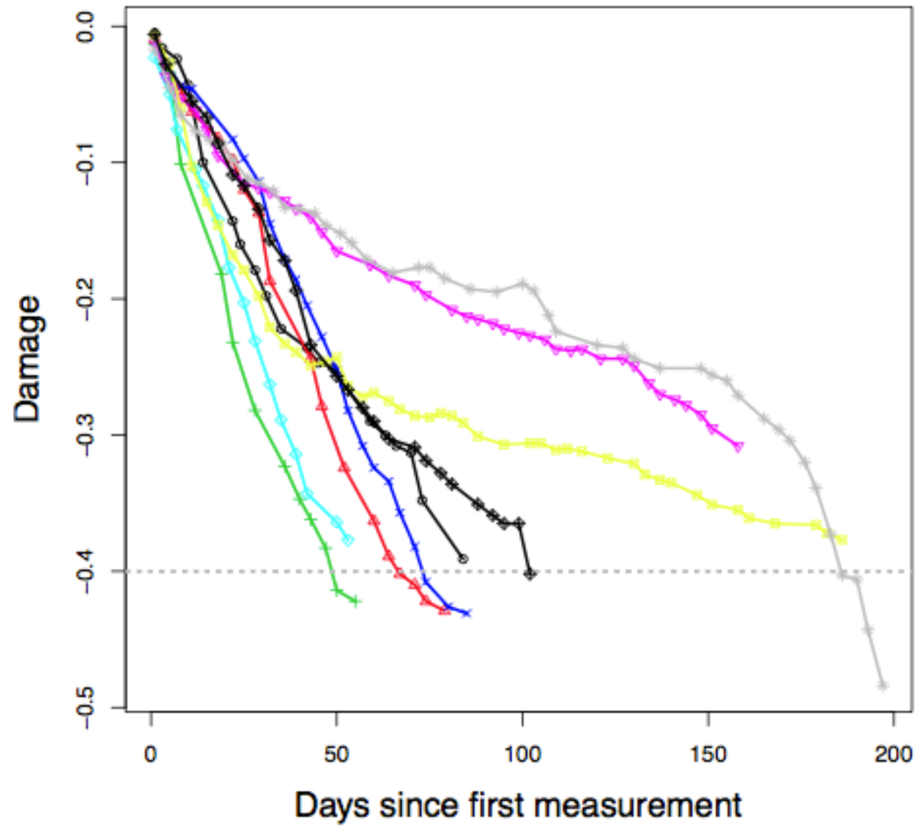
The outdoor temperature, humidity, and UV spectrum and intensity were recorded during the test period

Degradation Measurements

Damage measured using FTIR at intervals of several days

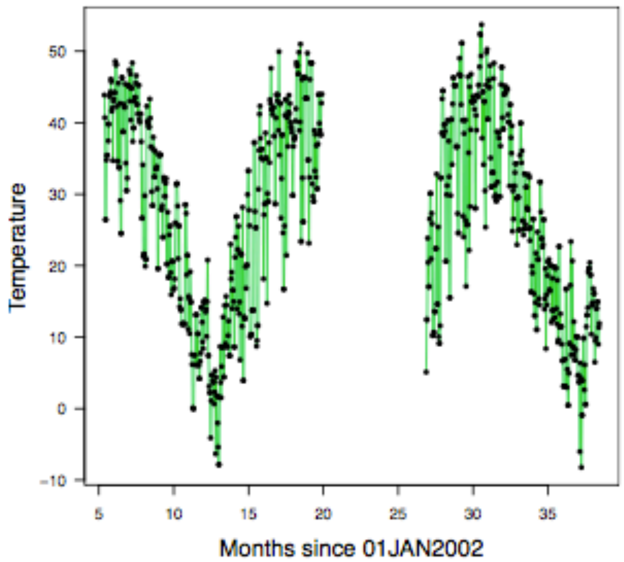
We consider degradation of aromatic C-O bonds (1250 cm^{-1} on the FTIR spectrum)

Failure threshold is $D_f = -0.4$ (level where there would be customer perceivable loss of gloss)

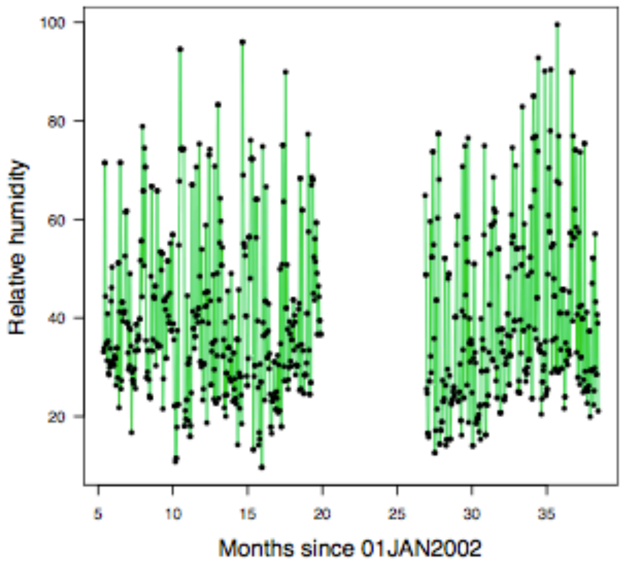


Degradation paths for nine representative specimens

Dynamic Temperature and RH Information



Daily Temperature



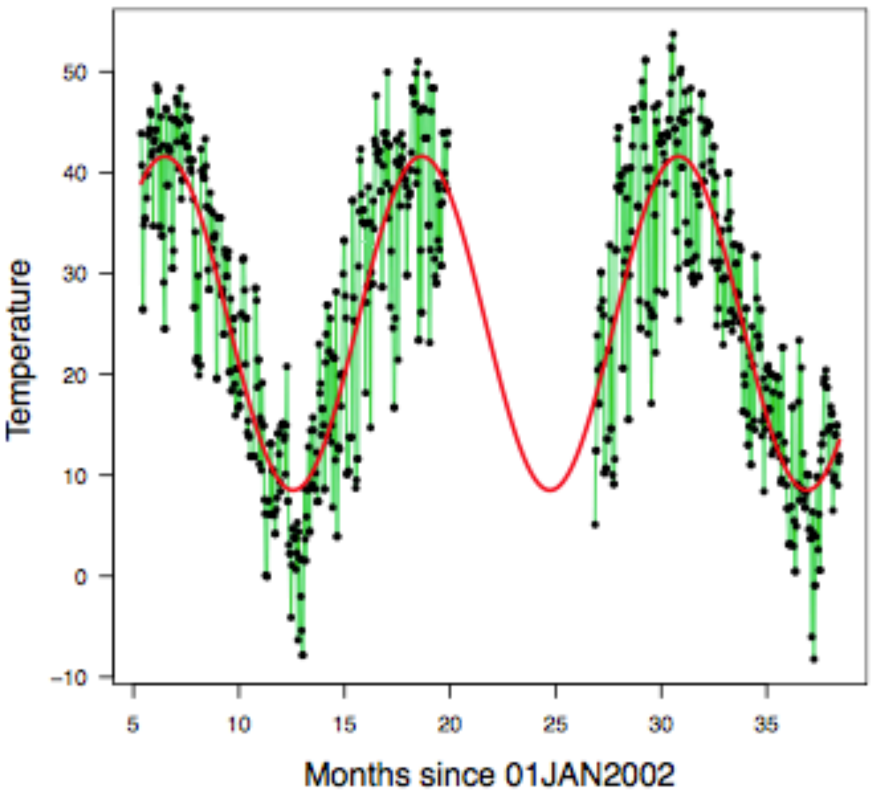
Daily RH

Environmental covariates show seasonal patterns

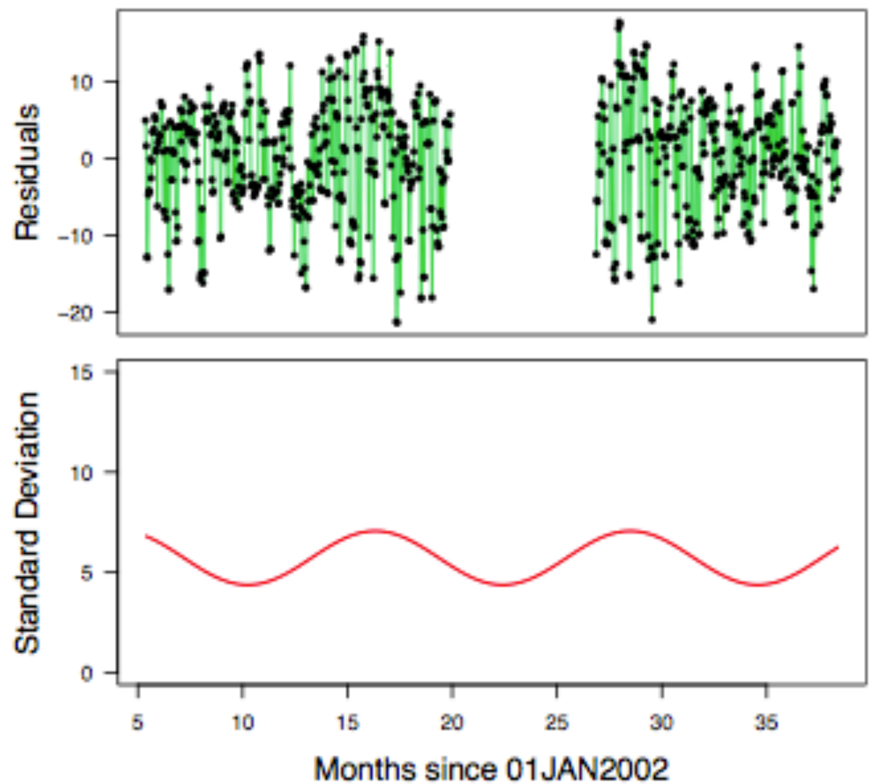
UV dosage shows more variability during summers

Due to different starting times, each group has its own dynamic covariate profiles, and thus different degradation rate profiles

Fitted Mean and Variance Structure for Temperature



Daily temperature



Residuals and estimated SD

General Additive Model

General additive model to incorporate dynamic covariate into the degradation path model

$$y_i(t_{ij}) = D[t_{ij}; \boldsymbol{x}_i(t_{ij})] + R(t_{ij}; \boldsymbol{w}_i) + \varepsilon_i(t_{ij})$$

$$D[t_{ij}; \boldsymbol{x}_i(t_{ij})] = \beta_0 + \sum_{l=1}^{p} \int_0^{t_{ij}} f_l[x_{il}(\tau); \beta_l] d\tau$$

β_0 is the initial degradation level

β_l is the parameter vector for the effect of covariate l

The coefficient vector is $\boldsymbol{\beta} = (\beta_0, \beta_1', \ldots, \beta_p')'$

$R(t; \boldsymbol{w}_i)$ is a monotone function of t. A simple but useful form is $R(t_{ij}; \boldsymbol{w}_i) = w_{0i} + w_{1i} t_{ij}$ where the random effect $\boldsymbol{w}_i = (w_{0i}, w_{1i})'$ describes unit-to-unit variability.

$\varepsilon_i(t_{ij})$ is the noise term.

Failure-time Distribution

The failure-time distribution provides the reliability information for an unobserved population

Given covariate process $\boldsymbol{X}(\infty) = \boldsymbol{x}(\infty)$ and individual random effect w, the degradation path is deterministic

The first crossing (failure) time $t_{\mathcal{D}}$ is
$t_{\mathcal{D}} = \min\{t : D[t; \boldsymbol{x}(\infty)] + R(t; w) = \mathcal{D}_f\}$

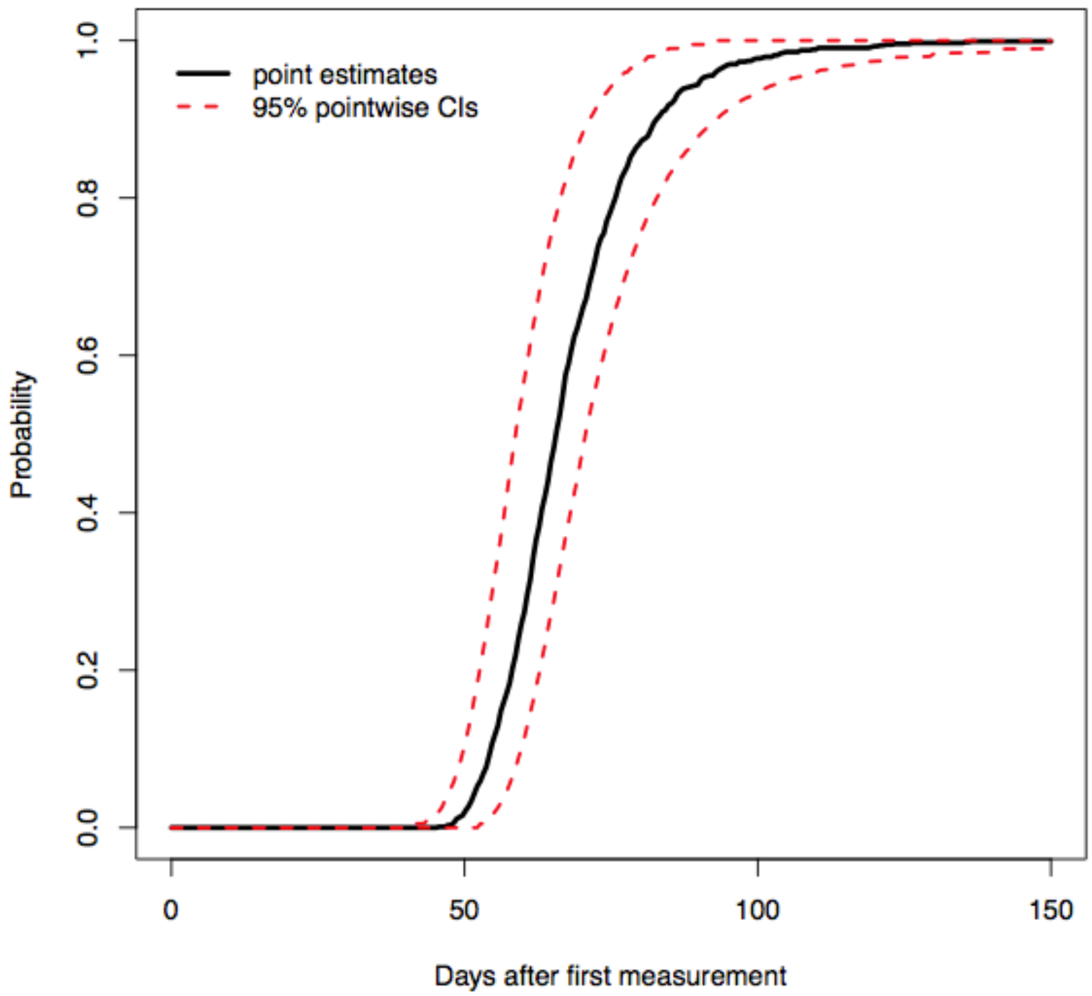
The first crossing time $t_{\mathcal{D}}$ is a function of D_f, $\boldsymbol{x}(\infty)$, and w.

Because $\boldsymbol{X}(\infty)$ and w are random, the first crossing time is a random variable

The cdf of $T = T[\mathcal{D}_f, \boldsymbol{X}(\infty), w]$ is
$F(t; \boldsymbol{\theta}) = \mathbf{E}_{\boldsymbol{X}(\infty)}\mathbf{E}_w \Pr\{T[\mathcal{D}_f, \boldsymbol{X}(\infty), w] \leq t\}, \quad t > 0$

Distribution of remaining life can be expressed in a similar way

Future Population Prediction Results



Generic Reliability Prediction Model

- Key Idea: ****Physics is mostly smooth and deterministic**;**
  variability is due to unit-to-unit differences and stochastic environment/use variables
- Model the reliability response, conditional on the observed covariate histories for each unit
  - Failure time data
  - Degradation data (perhaps visible above a detection limit or after initiation)
  - Success/Failure at age (quantal-response) data
- Model may be:
  - Simple (e.g., linear cumulative damage)
  - Physics-based (e.g., FEM fatigue crack growth)
- Develop a model for the covariate process history. For example:
  - Time series for environmental/use variables
  - Point process model for random shocks

  Possibly with seasonality or unit-to-unit random effects
- Predict future damage based on predictions of the covariate processes

Technical Needs for an Effective Reliability Prediction

- Well understood failure mode(s)
- Model for the relationship between the reliability-data response for individual units' covariate histories
- Definition of failure in terms of the reliability-data response
- Ability to predict covariates for individual units

Empirical modeling can, to some extent, make up for limited knowledge about the physics of failure and the effect of covariate histories

Concluding Remarks

- Reliability models that use rate/environmental dynamic covariate information and realistic physics-based computer models have the potential to improve safety and reduce costs.

- Predictive models can be built on the basis of either failure-time data, degradation data, or success/failure at age data.

- Use of physics-based computer models can be useful (or essential), especially when extrapolation is needed

- Key tasks are to:
  - Model the relationship between failure (or damage) and the dynamic covariates
  - Develop a model for the dynamic covariates

- The increased availability of covariate data from systems implies the need for more involvement of statisticians in the analysis and modeling of reliability/SOE data.

References

[1] Meeker, W.Q. and Escobar, L.A. (1998), *Statistical Methods for Reliability Data*. John Wiley and Sons, Inc.

[2] Hong, Y., Meeker, W. Q., and McCalley, J. D. (2009), Prediction of Remaining Life of Power Transformers Based on Left Truncated and Right Censored Lifetime Data. *Annals of Applied Statistics*, 3 857-879.

[3]Hong, Y. and Meeker, W.Q. (2010), Warranty Prediction Based on Auxiliary Use-rate Information. *Technometrics* 52, 148-159.

[4]Hong, Y. and Meeker, W.Q. (2013) Field-Failure Predictions Based on Failure- Time Data with Dynamic Covariate Information. *Technometrics*, 55, 135-149.

[5]Li, M. and Meeker, W.Q. (2013) Application of Bayesian Methods in Reliability Data Analyses. The *Journal of Quality Technology*, 45, xxx-xxx (in press).

[6] Meeker, W. Q. and Hong, Y. (2014), Reliability Meets Big Data: Opportunities and Challenges (with discussion). To appear in *Quality Engineering*.

[7]Fischer, K., Stalin, T., Ramber, H., Wenske, J. Wetter, G., Karlsson, R., and Thringer, T., (2014) Field- Experience Based Root-Cause Analysis of Power-Converter Failure in Wind Turbines, *IEEE.*

[8[Hong, H.,Duan, Y., Meeker, W.Q., Stanley, D., and Gu, X.,(2014), Statistical Methods for Degradation Data with Dynamic Covariates Information and an Application to Outdoor Weathering Data, *Technometrics*

Slides 18,19, 22-45 created by Dr. William Q. Meeker (largely based on [4], [6], and [8])

QUESTIONS