Wind Energy Operations & Maintenance

A brief look into industry's view on using big data

Prepared for:
WESEP 594 and
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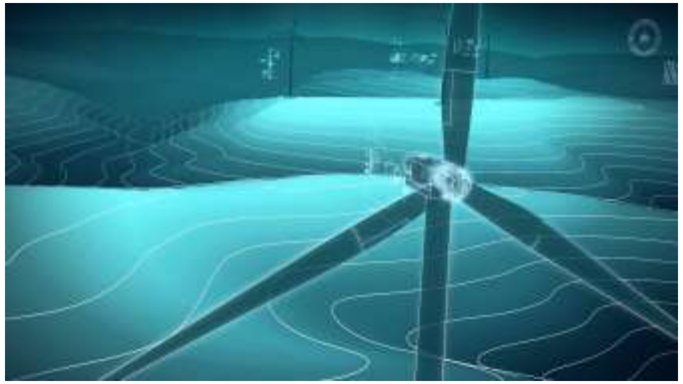

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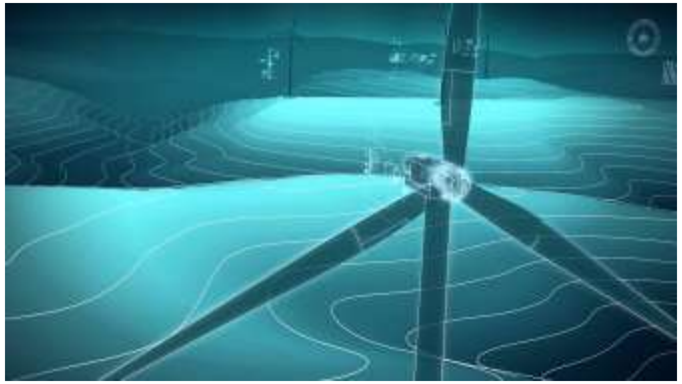


Outline

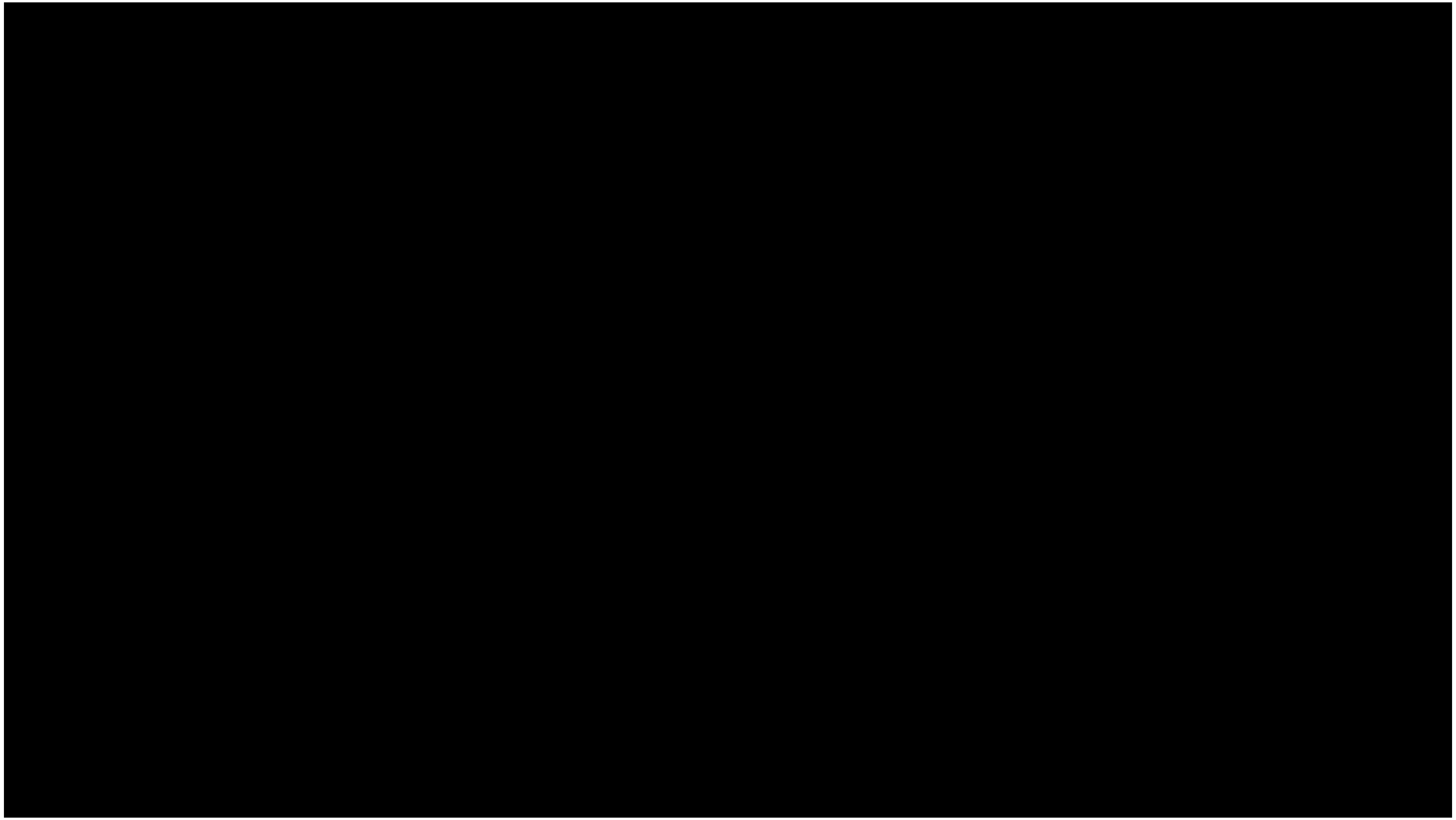
- **Operations and Maintenance Overview**

- **Big Data Overview**

- **Industry challenges in an evolving market**
  - **Owner perspectives on policy and market positioning**
  - **Owners and operators use of data**

- **My research**
  - **A brief look into one of my research projects.**
  - **Small-scale wind turbine recurrence modeling**

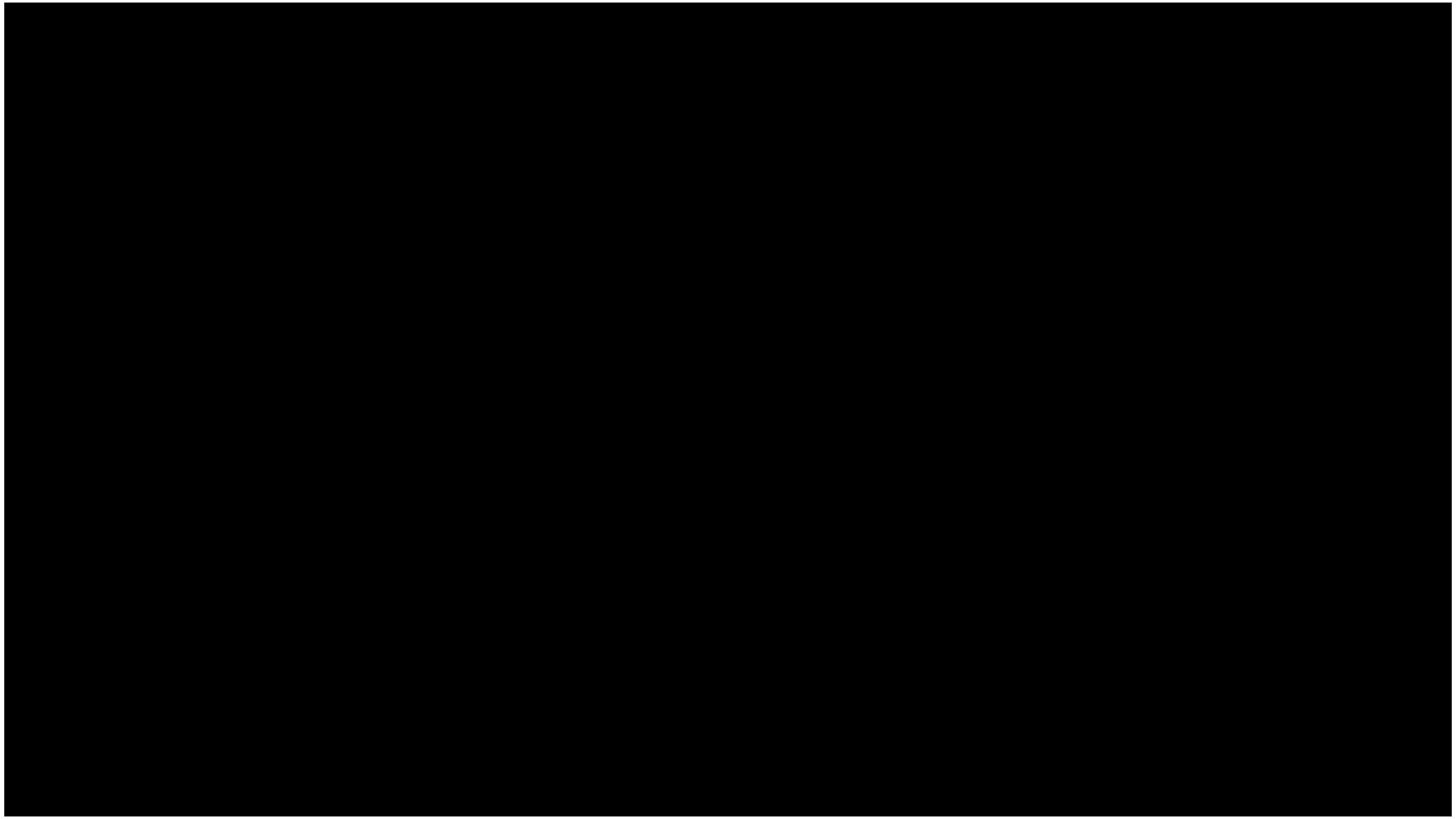
Motivating Big Data in the 21st Century



Netflix Example

•When you pause, rewind, or fast forward
•What day you watch content (Netflix has found people watch TV shows during the week and movies during the weekend.)
•The date you watch
•What time you watch content
•Where you watch (zip code)
•What device you use to watch (Do you like to use your tablet for TV shows and your Roku for movies? Do people access the Just for Kids feature more on their iPads, etc.?)
•When you pause and leave content (and if you ever come back)
•The ratings given (about 4 million per day)
•Searches (about 3 million per day)
•Browsing and scrolling behavior
•Netflix also looks at data within movies. They take various "screen shots" to look at "in the moment" characteristics. Netflix has confirmed they know when the credits start rolling; but there's far more to it than just that.
•These characteristics may be the volume, colors, and scenery that help Netflix find out what users like.

Motivating Big Data within Industry



Background

- Enhancing the reliability of wind turbines
  - Collaborative effort between industry and academia for 20+ years
- DOE's vision

Limited work from 2010 – 2015 in applying reliability-based statistical methodologies

- Fischer, Besnard, and Bertlin (2011)
  - Reliability centered maintenance study that utilizes failure data and industry expert opinions to improve the reliability, availability, and profitability of wind turbines
- *Reliawind:* Wilkinson (2012)
  - Identifies critical failure modes and summarizes SCADA system potential
- Arifujjaman and Chang (2012)
  - Component-specific reliability anlysis on grid-connected permenant magnet generator-based wind turbines.

Background

- Tjernberg and Wennerhag (2012)
  - Compilation of reports that survey the development and research needs for wind turbine O&M
- Hussain and Gabbar (2013)
  - Focus on predicting gearbox health using a nonlinear autoregressive model with exogenous inputs
- Godwin and Matthews (2013)
  - Develop classification methods to detect wind turbine pitch faults using SCADA data
- Al-Tubi, Long, Tavner, Shaw, and Zang (2015)
  - Investigate the probabilistic risk of gear flank micropitting risk with the use of SCADA data.

During 2014 – 2015 we started to see an advancement in the reliability-based methods being using in the wind energy industry.

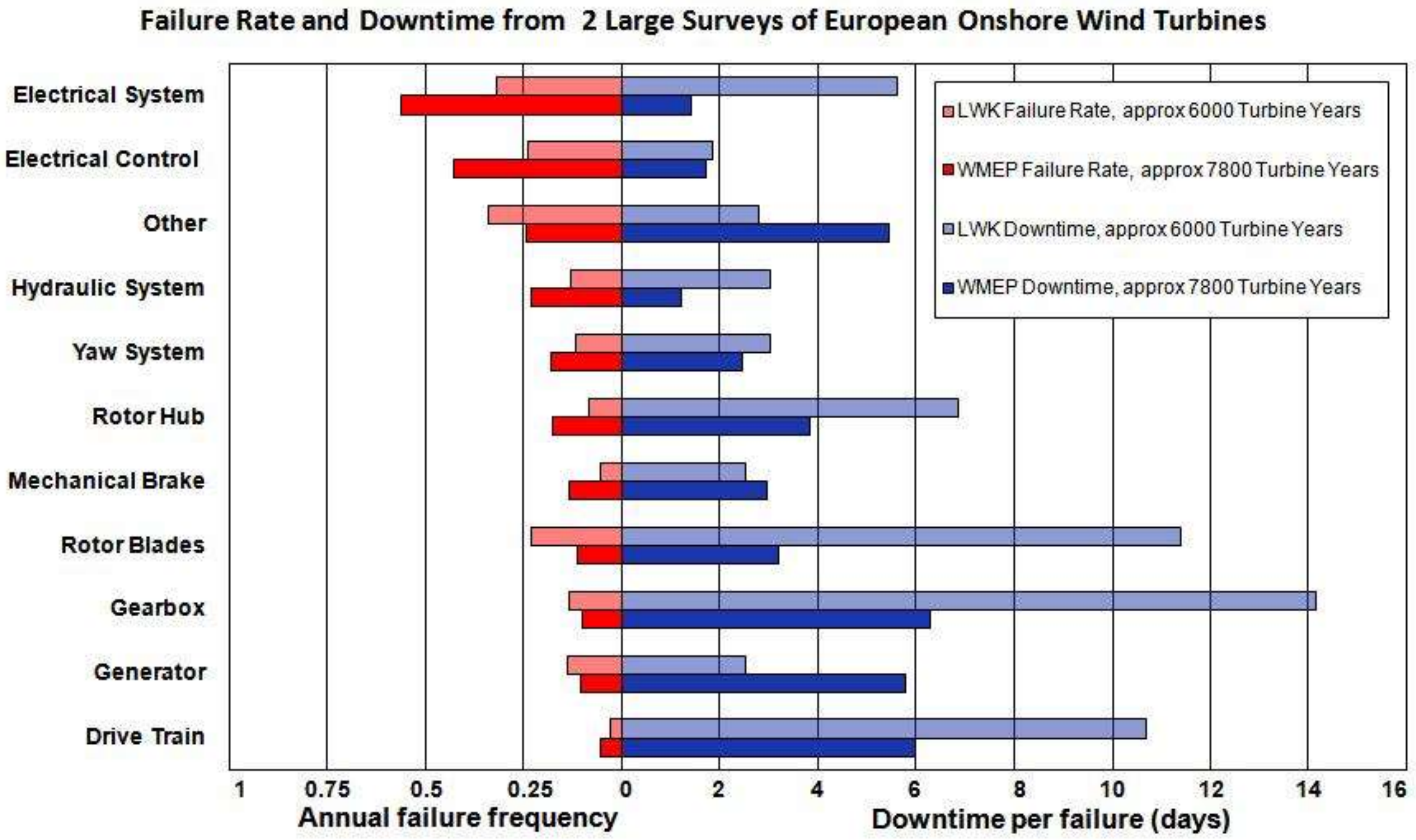
Examples

Wu and Mueller (2014): Reliability analysis for small wind turbine using bayesian network

Wu, Butler, and Mueller (2016): Reliability analysis for small wind turbines using bayesian hierarchical modelling: the effect from the repair mechanism and environmental factors

Wu (2017): combining fatigue analysis information into reliability analysis using bayesian hierarchical modeling

Background



Failure Rate and Downtime from 2 Large Surveys of European Onshore Wind Turbines
Electrical System
Electrical Control
Other
Hydraulic System
Yaw System
Rotor Hub
Mechanical Brake
Rotor Blades
Gearbox
Generator
Drive Train
LWK Failure Rate, approx 6000 Turbine Years
WMEP Failure Rate, approx 7800 Turbine Years
LWK Downtime, approx 6000 Turbine Years
WMEP Downtime, approx 7800 Turbine Years
1
0.75
0.5
0.25
0
2
4
6
8
10
12
14
16
Annual failure frequency
Downtime per failure (days)

Improving Reliability

- Assist in preventing catastrophic events
- Uptower repair instead of replacement
- Uptower repair instead of downtower repair
- Effective spare parts management (JIT)
- Resource mitigation (personnel and equipment)

Big Data in the Wind Energy Industry

- Wind turbines commonly outfitted with many sensors
  - Environmental and operational conditions
  - 125 – 400 sensors
  - 2000 observations per minute
  - Single turbine: 1 terabyte of data per week
  - Time series
- Example literature that has utilized big data
  - Ciang (2008) and Faulkner (2012)
    - Describe the use of sensor data for system health monitoring
  - Tautz – Weinert and Watson (2016)
    - Provide a review on using SCADA data for wind turbine condition monitoring
- Can yield great benefits
  - Forecasting power
  - Develop cost analysis strategies (short/long term)
  - *Wind Power Monthly's Expert Report* (2014)
    - Explains the growing sophistication of SCADA data.
  - Information on turbine state
    - Programmable logical controllers (PLCs)
    - Predefined tolerances
    - State change
    - Alarms: Precursor to failure
    - Minimize financial burdens from unplanned maintenance

Table 1. Examples of data logged by SCADA systems.

Subsytem	Data Collected
Rotor and Blades	Pitch angle and rotor speed.
Gearbox	Oil, bearing, and hydraulic temperatures. Vibration, force, and rotational speed.
Generator	Stator and rotor voltages and currents. Power factors, rotor and grid frequencies, cabinet temperature, and generator speed.
Nacelle	Position, frame temperature, yaw break pressure, etc.

Key Feature of Wind Energy Field Data

- Large vectors of time series data are periodically recorded
  - Study differences between wind turbines at the individual/fleet levels
  - System operating/environmental (SOE) data
  - Potential to increase the reliability and availability of wind turbines with a minimal cost.

SCADA Data Analysis vs. Condition Monitoring

Industry is using SCADA to

- Turbine production efficiency
- Drivetrain bearing temperature outliers
- Gearbox oil pressure and temperature
- Turbine fault and hard stop counts
- Torque reversal events – grid faults
- Correlate to vibration data
- Yaw misalignment

Condition Monitoring

- Vibration based
- Accelerometer sensors
- Gears, bearings, shafts
- Condition Monitoring

SCADA Data Analysis

- Operating parameters
- 200 – 400 sensors per turbine
- Temperature, power, RPM, …

A Data-led, cost driven, and repowering surge

- Increasing investments in data analytics
  - Moving from reactive maintenance to predictive maintenance
  - Reduce energy losses and labor costs
- Repowering boom
  - Term comes from fossil fuel sector
    - Complete or partial replacement of items like boilers
    - Done to improve output and efficiency and bring down
      - Emissions
      - Costs
  - In 2015, only 600 MW of US capacity installed for 20+ years
  - 10 year PTC plan has enhanced repowering interest
  - 10 GW of US capacity between 10 – 20 years old

Repowering will allow operators to replace less reliable units with supported new models that raise efficiency and lower the cost of energy
Matt Coleman
Senior Director Vestas

The federal PTC will continue to support wind power construction until 2020 and digital innovations along with higher-performance turbines will drive down costs
Andy Holt
GE General Manager

We are going to have big years. For all the OEMs our job is to develop a turbine for the 2020/2021 timeframe that moves into $.03/kWh and that moves into unsubsidized spaces. - *Andy Holt*

The Power of Data in the Wind Industry

The last two or three years have been the most disruptive of the last 50 years in power generation when it comes to services and new equipment.

Mark Albenze
Siemens CEO

The transformed power market will require our industry to deliver more than LCOE, we must deliver market value proposition of affordable capacity and energy but be flexible to match market conditions.

Mark Albenze
Siemens CEO

We can offer higher availability, condition-based maintenance, proactively executing work to align with mark conditions, offer module surfaces, and shift to intelligent services that automatically respond to conditions, optimize production and manage wear and tear.

Mark Albenze
Siemens CEO

Operational Challenges in an Evolving Market

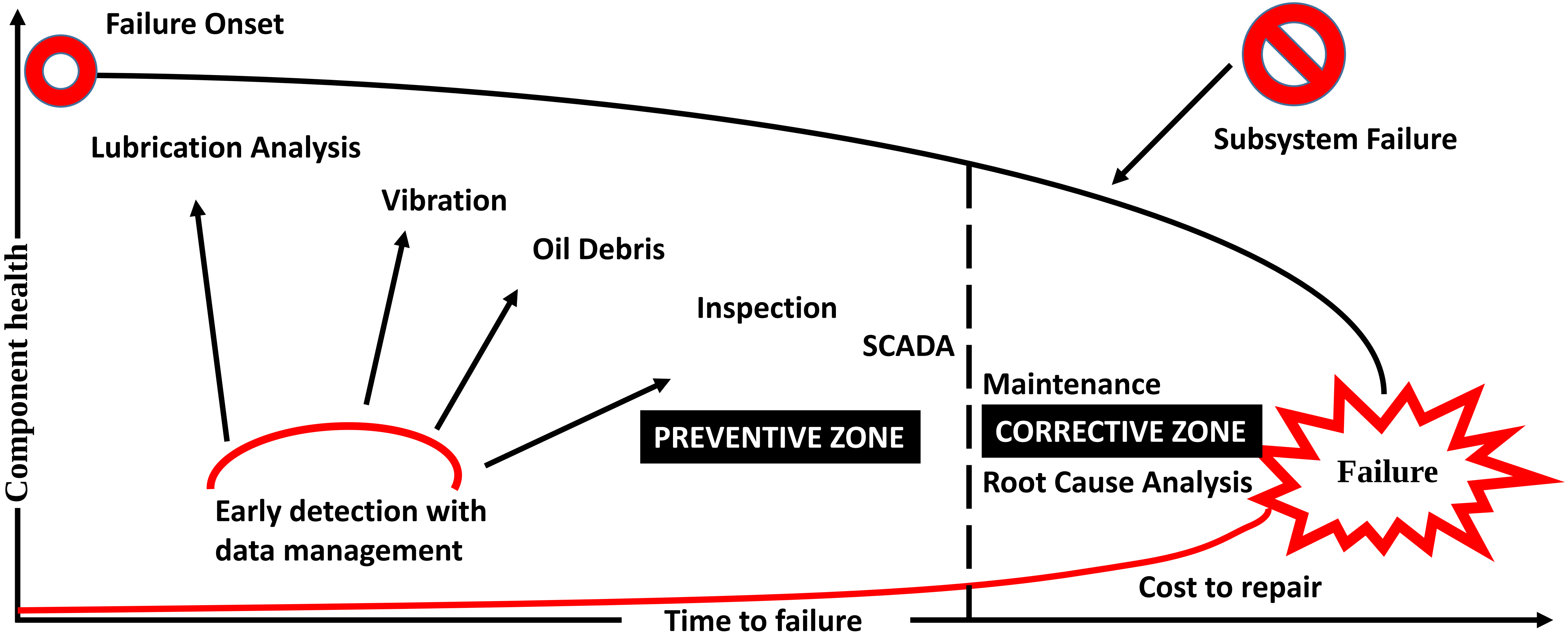
- Over 400 sensors with over 200 GB of data each day.
  - E.ON Energy is evaluating over 21 trillion observations and turning big data into valuable insights.

- Shift from reactive to proactive maintenance.
  - E.ON has 60,000 years of insight
  - Detected 19,000 systems avoiding failure

- Industry challenges in an evolving market
  - Owner perspectives on policy and market positioning
  - Owners and operators use of data

- Hermes Blade Inspection Program
  - Use high imagery from drone and ground based cameras
- Self-learning turbines are an attractive option, allowing expert knowledge to be incorporated into the model

Benefits of Using Data and Condition Monitoring



Small-Scale Turbine Recurrence and Cost Modeling as a Function of Operational Covariates from Supervisory Control and Data Acquisition Systems

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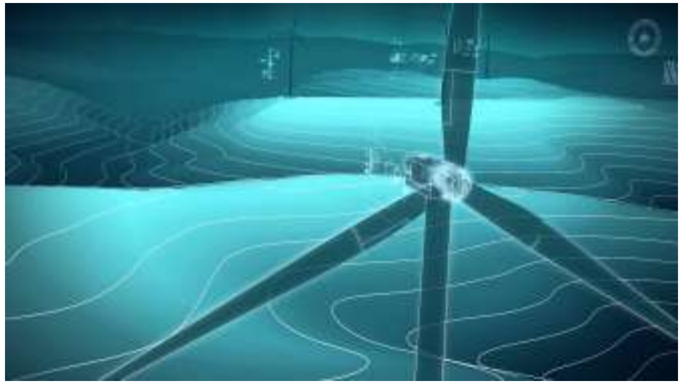

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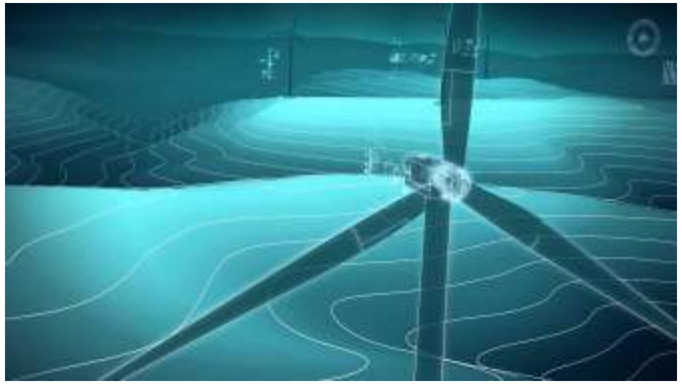
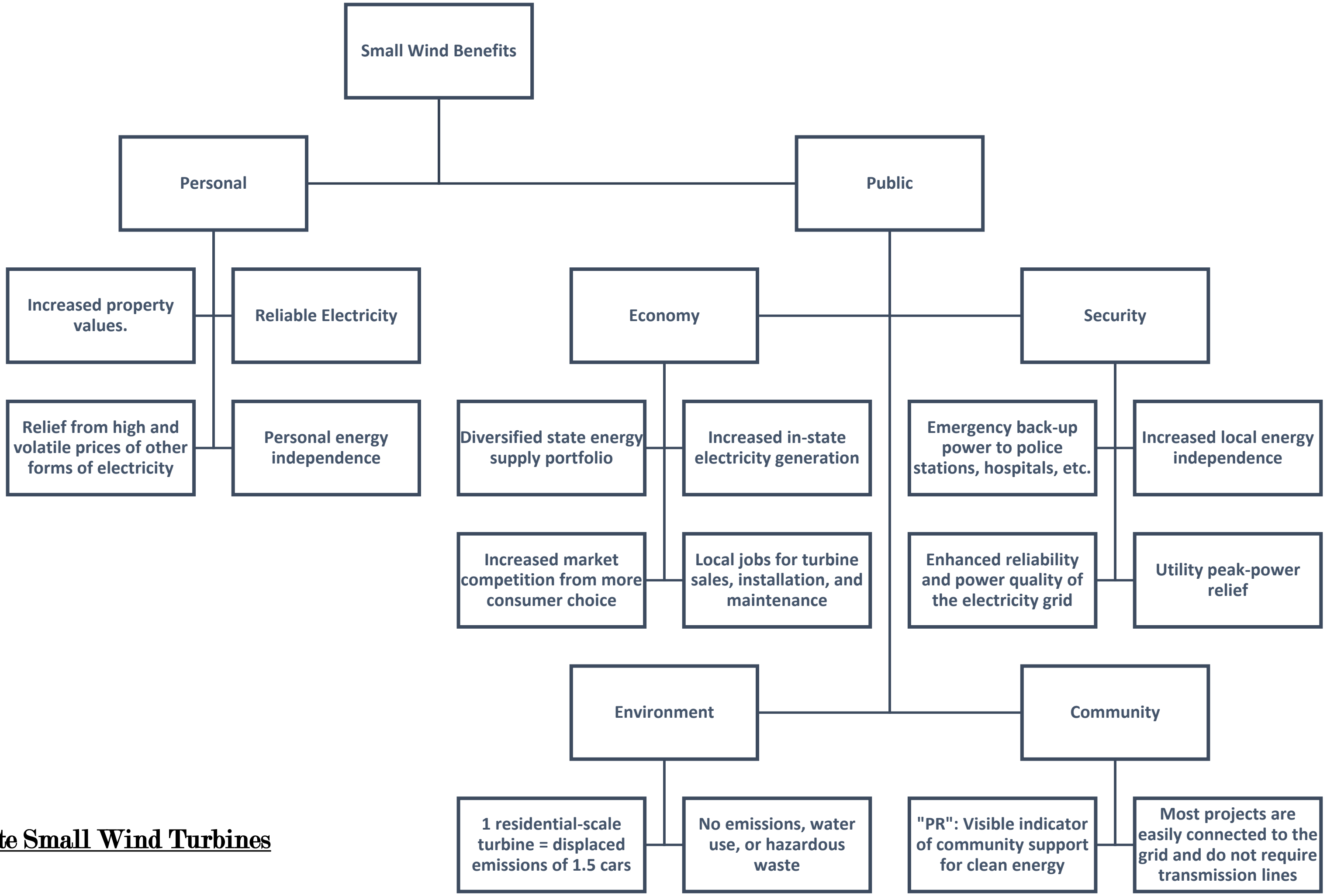


Why Small Wind?

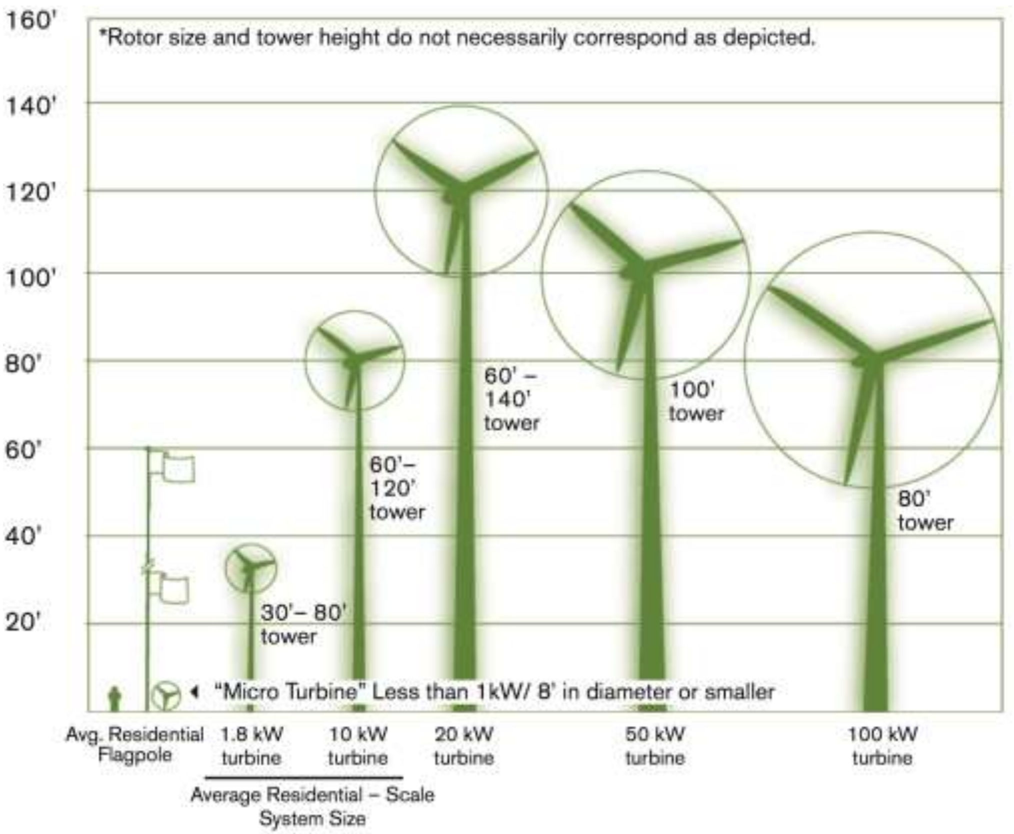


Summary of AWEA's Policies to Promote Small Wind Turbines
Flowchart by: Michael S. Czahor

What are Small Wind Turbines?

Background Information

- Over 200 different models exist
- Approximate tower heights range from 30 – 150 feet
- Tower types: monopole, lattice, and guyed monopole
- Horizontal and vertical axes are being used



Small Wind Certification Council (SWCC) Small/Micro wind display

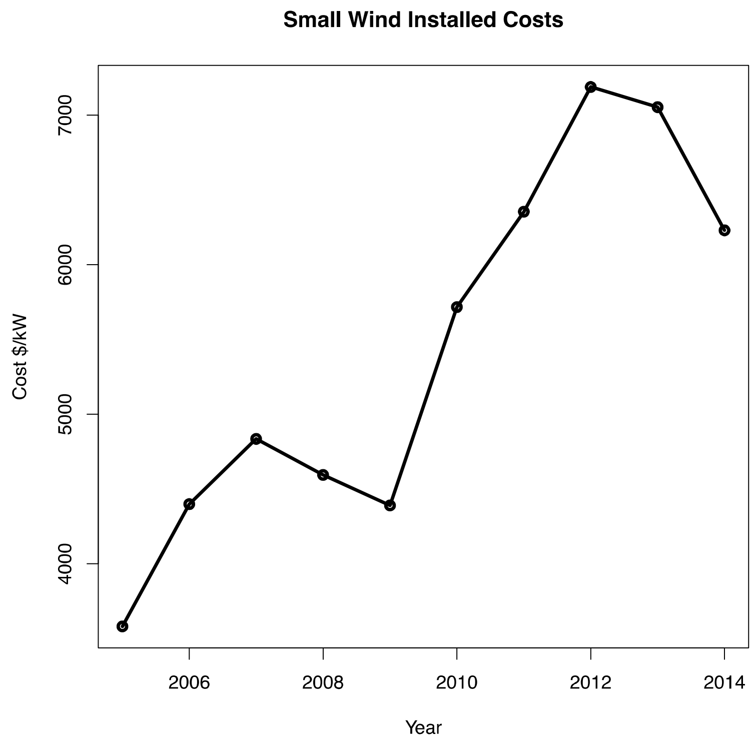
Small Wind in the 21st Century

Background Information

- SWTs saw less engineering advances that that of LWTs due to minimal funding for research.
- "Reliability has historically been the Achilles heel for small wind turbine technology". (Bergey, 2002)
- Clausen and Wood (2000) describe the early advances of SWT technologies.
- Increased popularity due to versatile makeup, allowing SWTs to be installed near households, schools, farms, remote locations, etc.
- Orrell and Foster (2015) reported that the average cost of SWT installation has decreased by $1,200/kW from 2013 to 2015.
    - Not as great as it sounds
- Since 2005 increases in labor costs, warranty contracts, price of material, etc.

Relevant Market Reports

- *Wind Technologies Market Report* (Wiser and Bolinger, 2015)
- *Distributed Wind Market Report* (Orrell and Foster, 2015)



Availability

Background Information

- Helps compare turbine-to-turbine performance

- "The fraction of a given operating period in which a wind turbine generating system is performing its intended services within the design specification." - International Electrotechnical Commission (IEC)
- Method used determined by owner and operator

    - According to Willams (2014), "a large majority of owners and operators do not have the capability to process terabytes of SCADA data to determine the true availability."

The most common method used in industry

- Based on time

$$A_{Time} = \frac{T_{Operation}}{T_{Period}} \quad (1)$$

- Easy to compute

- Deficiencies
    - Does not assist in poor planning of preventive maintenance

    - Does not detect the impacts of wind speed during corrective maintenance

    - Does not detect performance issues when a wind turbine is running.

Project Overview

Data Source

N = 21 NPS 100-21 wind turbines

Rotor size: 21 meters
Possible tower sizes: 23, 30, or 37 meters
Operational frequencies: 50 Hz or 60 Hz.

General Configuration	
Model	100-21
Design Class	IEC WTGS IIA
Power Regulation	Variable Speed; stall control
Orientation	Upwind
Yaw Control	Active
Number of Blades	3
Rotor Diameter	20.7 meters (68 feet)
Performance	
Rated Electrial Power at standard conditions	100 kW
Rated Shaft Speed (Standard Turbine)	58.6 RPM
Rated Shaft Speed (Arctic Turbine)	56.3 RPM
Cut-in Wind Speed	3.0 m/s (7 mph)
Rated Wind Speed	15.0 m/s (36 mph)
Cut-out Wind Speed	25.0 m/s (56 mph)
Noise	55 dBA at 40 meters from nacelle

Table 1: NPS 100-21 General Information

NPS Wind Turbine Data

Data Source

- N = 21 NPS 100-21 wind turbines.

21 csv files imported to R.

10-minute averages of covariates from the time of installation through October 28th, 2016.

State Vector

Turbine State Enumeration	
State	Integer Value
Init	0
Off	1
Stopped	2
System Test	3
Wait	4
Motor	5
Standby	6
Active	7
Decelerate	8
Service	9

21 CSV files

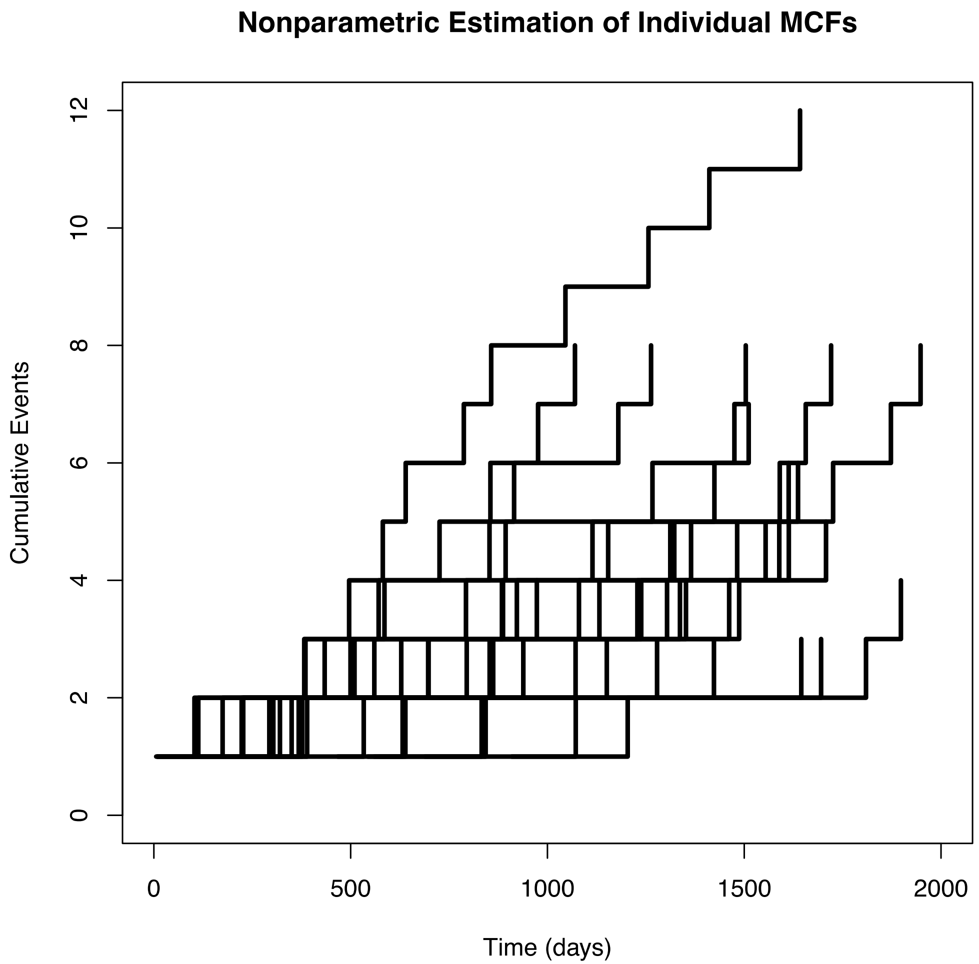
- Timestamps (every 10 minutes from time of installation)
- 12 unique covariates in addition to MAX and MIN readings over each interval
  1) R_YawVaneAvg_deg
  2) R_YawPosition_deg
  3) R_Windspeed_mps
  4) R_TurbineState
  5) R_TempAmb_degC
  6) R_TempFrame_degC
  7) R_TempGen1_degC
  8) R_TempGen2_degC
  9) R_TempIGBTinv_degC
  10) R_TempIGBTrec_degC
  11) Rotorspeed_rpm
  12) InvPwr_kW

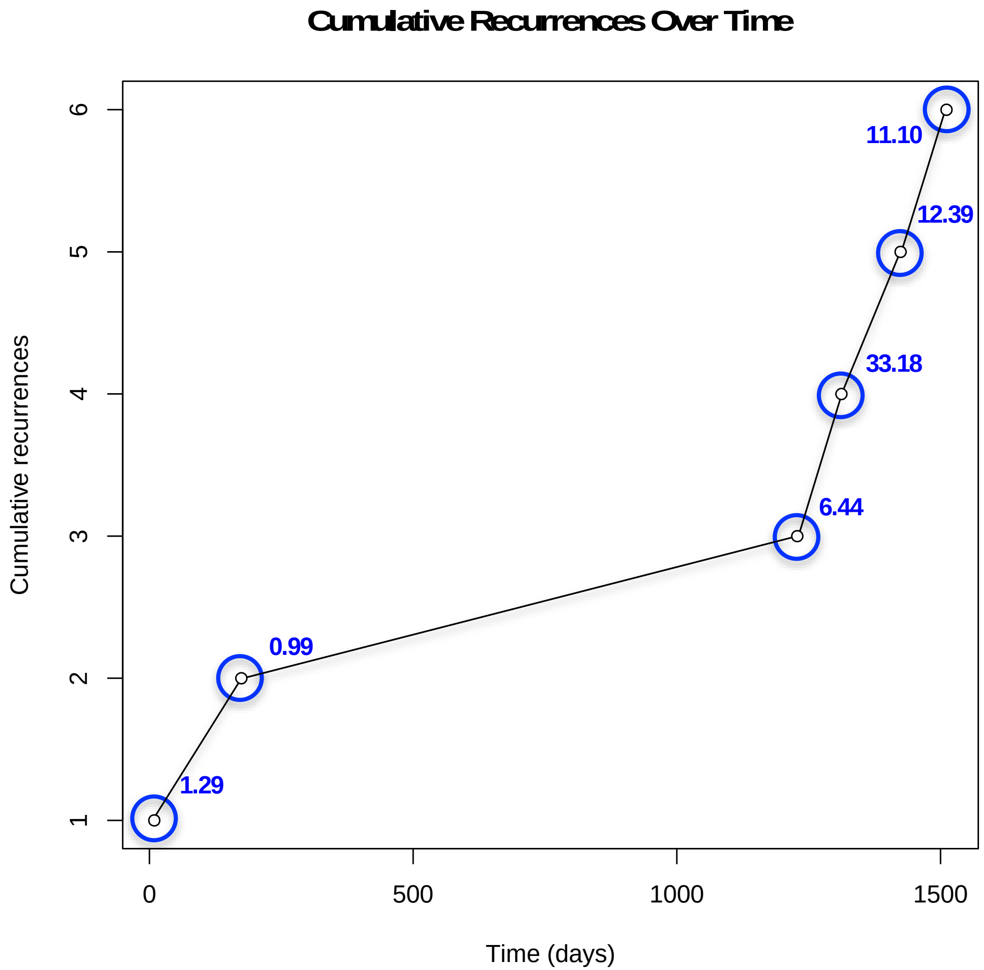
A Brief Look at the Data

- Data collected over four year period
- Common data freeze data (DFD)
- State code of 9 = service event
  - Preventive maintenance
  - False alarm
  - Corrective maintenance
- Downtime
  - Each service event results in a cost (downtime)

- $J = 21$ Wind turbines $j \in 0, \dots, 21$.
- Event information with timestamps.
- Cost associated with each event.
- Individual use rate information.
- Data freeze date (October 2016).

A Brief Look at the Recurrence Data



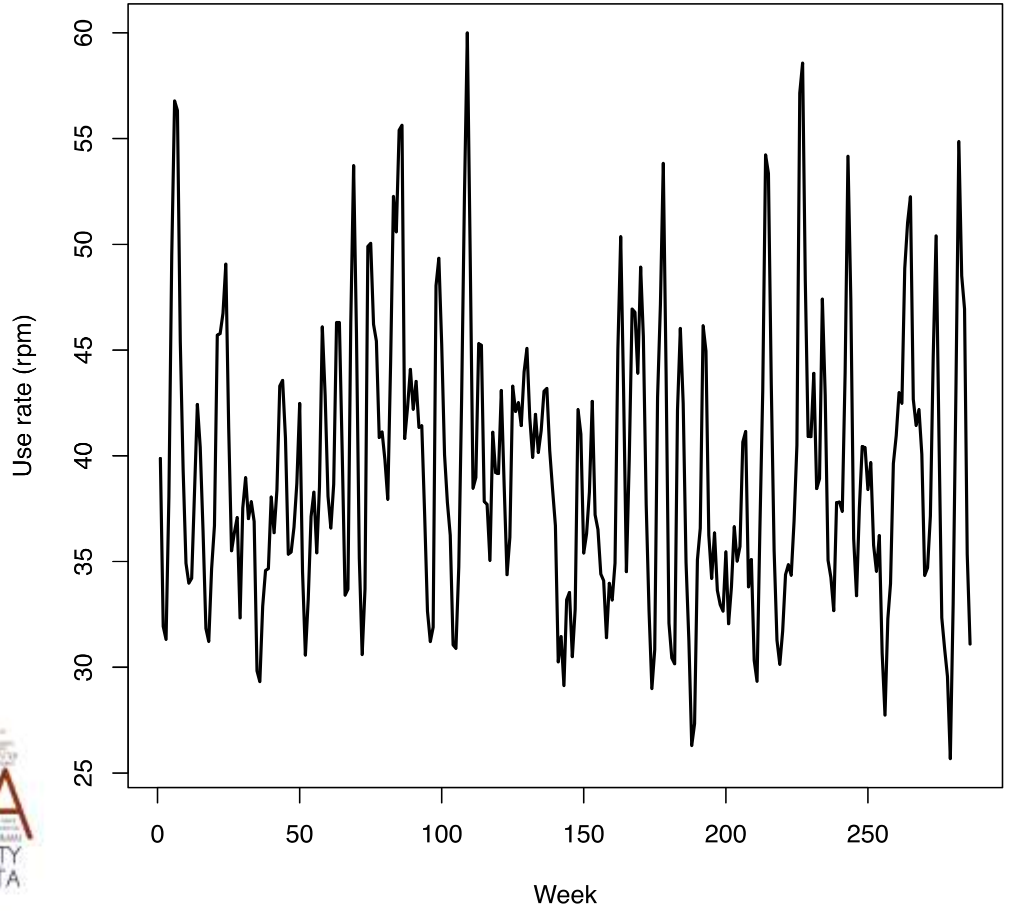


A Brief Look at Dynamic Covariate Data

For each of the $j \in 0, \ldots, 21$ wind turbines, dynamic covariate data is measured, resulting in individual covariate histories for each wind turbine. Let

- $X(t) = [X_1(t), X_2(t), \ldots, X_p(t)]$ represent the operational and environmental covariate history at time t, where p is the number of covariates and
- $X(t) = \{X(s) : 0 \leq s \leq t\}$ represent the history of the covariate process , which logs dynamic covariate data on the interval $(0, t]$

For the $J = 21$ wind turbines, we denote the value of covariate w for wind turbine j at time s as $x_{jw}(s)$. An individual wind turbine's covariate history is denoted by $x_j(t_{jn_j}) = \{x_j(s) : 0 < s < t_{jn_j}\}$, which logs each dynamic covariate from time 0 to t_{jn_j} for wind turbine j (Hong, Duan, and Meeker, 2014).



Service Event Model

Nonhomogeneous Poisson Process

$$v(t;\phi,\eta) = \frac{\phi}{\eta}\left(\frac{t}{\eta}\right)^{\phi-1}, \phi,\eta > 0$$

$$\lambda(t) = E[N(t)] = \int_0^t v(u)du = \left(\frac{t}{\eta}\right)^{\phi}$$

$$L(\phi,\eta) = \left(\frac{\phi}{\eta}\right)^{r} \times \prod_{j=1}^{r} t_j^{\phi-1} \times \exp[-\mu(t_a:\phi,\eta)]$$

ML Estimates: $\hat{\phi} = \frac{r}{\sum_{h=1}^{r}\log(t_a/t_h)}, \hat{\eta} = \frac{t_a}{r^{1/\hat{\phi}}}$

Single Wind Turbine Model

$$\lambda = \lambda_j = \lambda(t_{c_j}) = \left(\frac{\eta}{c}\right)^{-\phi} \rightarrow \eta = c\lambda^{-1/\phi}$$

Hierarchal approach to make inference on $\theta = (\lambda,\phi)$

$L(DATA|\theta)\pi(\theta)$ with diffuse Jeffery's priors where

$$\pi(\lambda,\phi) \propto \frac{1}{\lambda\phi}$$

- $\lambda | t_1, \ldots, t_n, t_c \sim \text{Gamma}(n, 1)$
- $\phi | t_1, \ldots, t_n, t_c \sim \text{Gamma}(n, \sum_{i=1}^{n} \ln(t_a/t_i))$

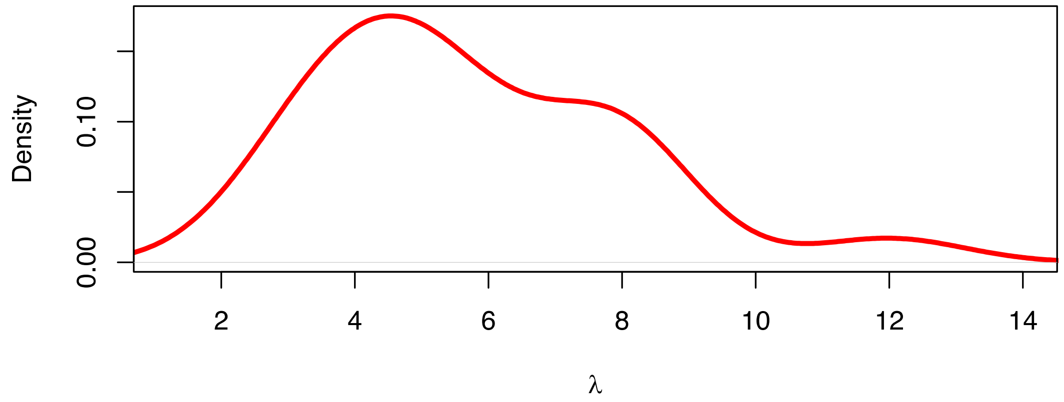
Service Event Model

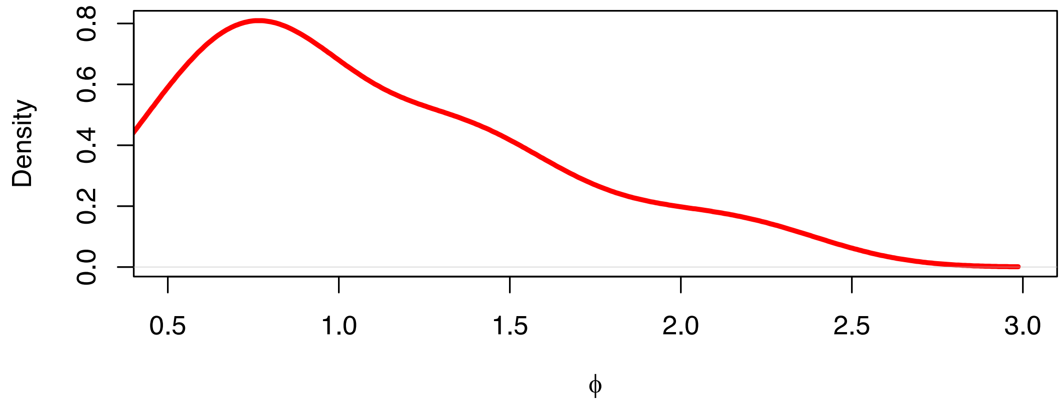
Multiple Wind Turbine Model

Hierarchical Modeling

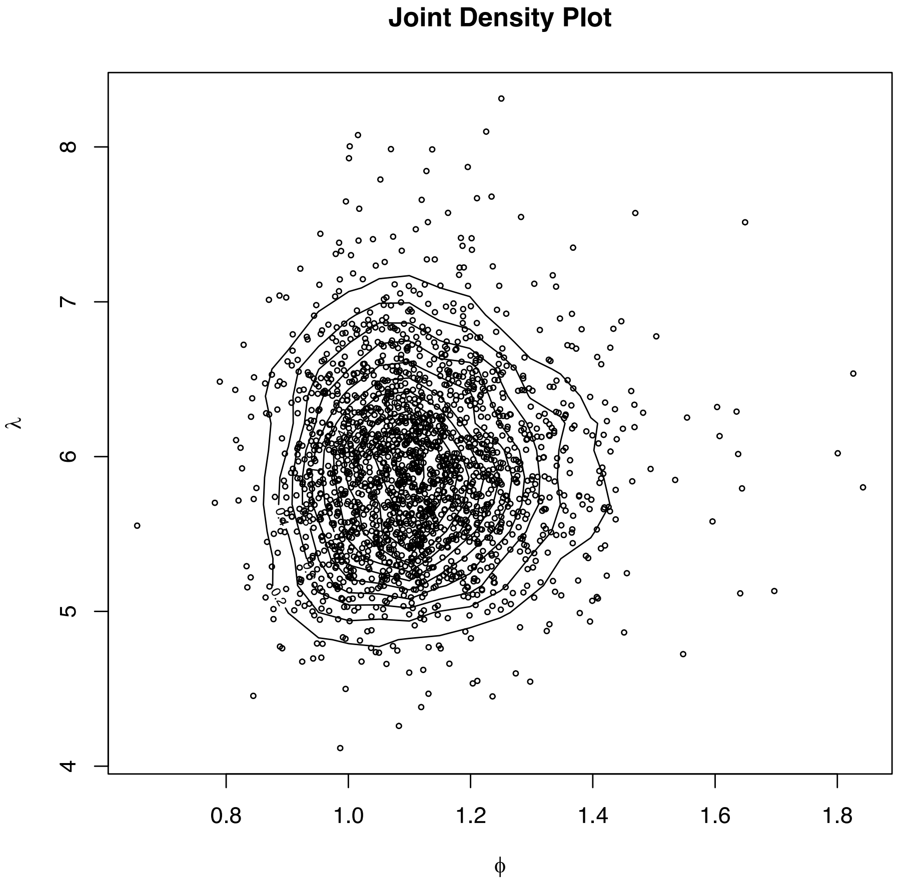
$$\lambda_j \sim \text{Gamma}(\alpha_\lambda, \beta_\lambda)$$
$$\phi_j \sim \text{Gamma}(\alpha_\phi, \beta_\phi)$$
$$\alpha_\lambda \sim \text{Gamma}(a_1, b_1)$$
$$\beta_\lambda \sim \text{Gamma}(a_2, b_2)$$
$$\alpha_\phi \sim \text{Gamma}(a_3, b_3)$$
$$\beta_\phi \sim \text{Gamma}(a_4, b_4)$$

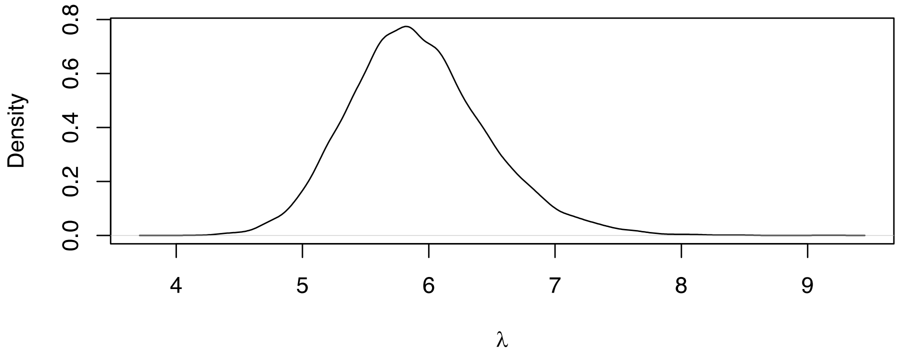
Diffuse priors let our analysis on the $J = 21$ wind turbines be data driven.

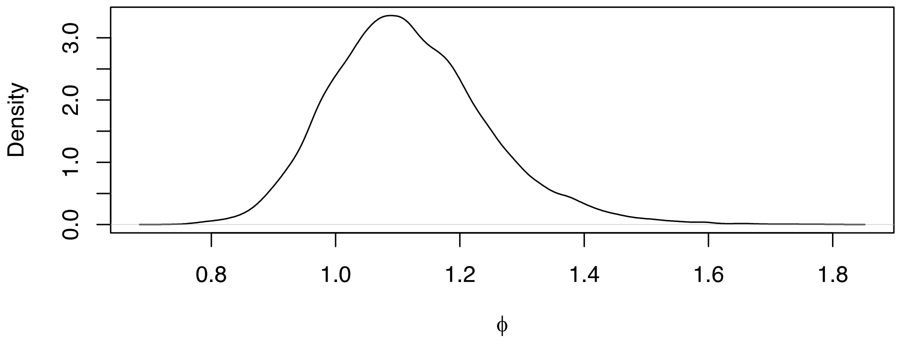




Service Posteriors







- Results were obtained using RJAGS.
- Parameters vary from turbine-to-turbine.
- Hierarchical model allows for a tradeoff between completely pooled analysis and an individual turbine analysis (Draper et al., 1992).
- Methods adapted from Ryan et al. (2011).

Table 2. NHPP posterior parameter output.

Parameter	Median	95% Credible interval
η_j	401.2	(282.2 , 607.2)
λ_j	5.868	(4.945 , 7.084)
ϕ_j	1.107	(0.895 , 1.408)

Cost/Use Rate Model

Log(cost) vs. Use Rate Relationship

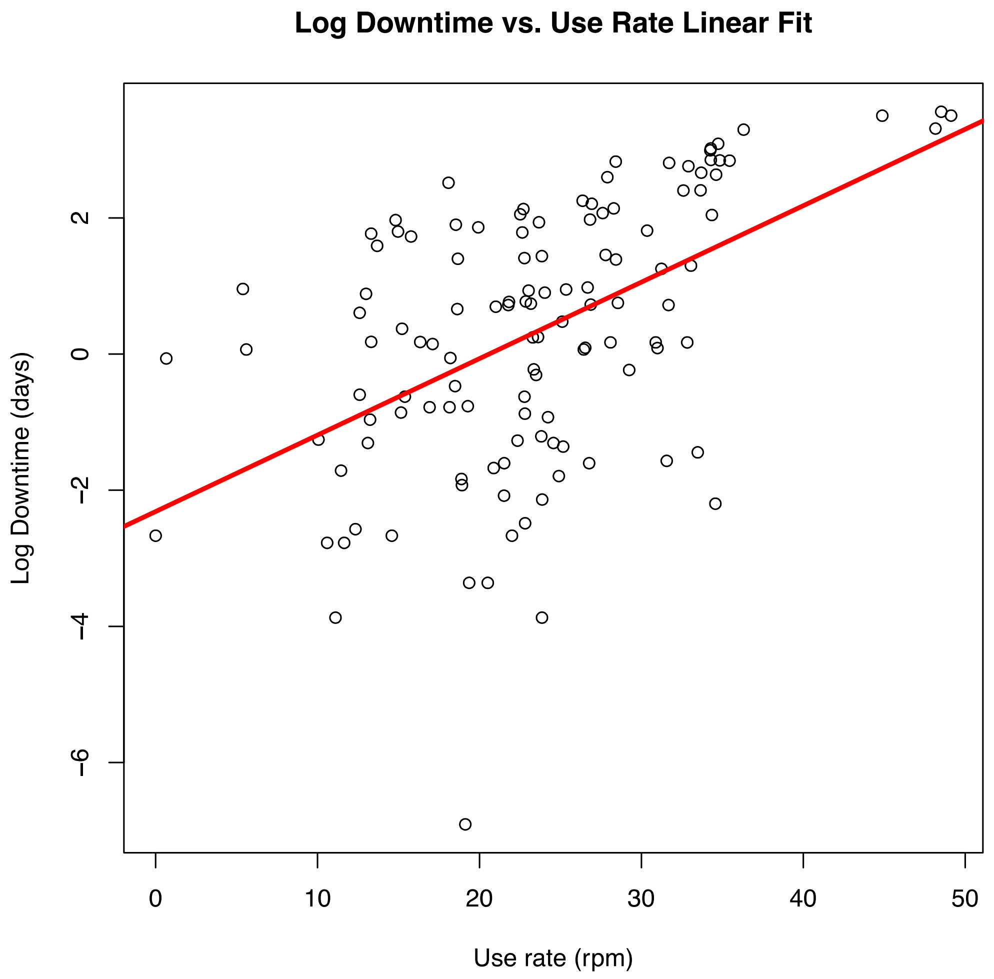
- 121 observed service events
- Linear relationship between
  Log($cost$) vs. *Use rate (rpm)*

- *Use rate* = two week turbine-specific rpm averages before service event.

$$Z_i = \beta_0 + \beta_1 \times U_i + \varepsilon_i$$

where $Z_i = \text{Log}(cost)$

$$\hat{z}_i = -2.31 + 0.11 \times u_i$$



Autoregressive Use Rate Model

<u>Autoregressive Use Rate Model</u>

- AR(2) model based on exploratory analysis of observed use rate time series.

$$U_t = \gamma_1 \; U_{t-1} + \gamma_2 \; U_{t-2} + \varepsilon_t, \varepsilon_t \sim N(0, \tau^2)$$

<u>Autoregressive Model in JAGS</u>

$$\pi(\tau^2, \gamma_1, \gamma_2 | \; U_1, \dots, U_t)$$

$$= f(\; U_1, \dots, \; U_t \,|\tau^2, \gamma_1, \gamma_2) \; \pi(\tau^2) \; \pi(\gamma_1, \gamma_2)$$

- Metropolis Hastings (MH) is an appropriate approach since full conditional distributions become non-standard densities.
- MH is lengthy, so we use JAGS.
- Diffuse uniform priors for γ_1, γ_2.
- Gamma prior for τ^2.

Use Rate Posteriors

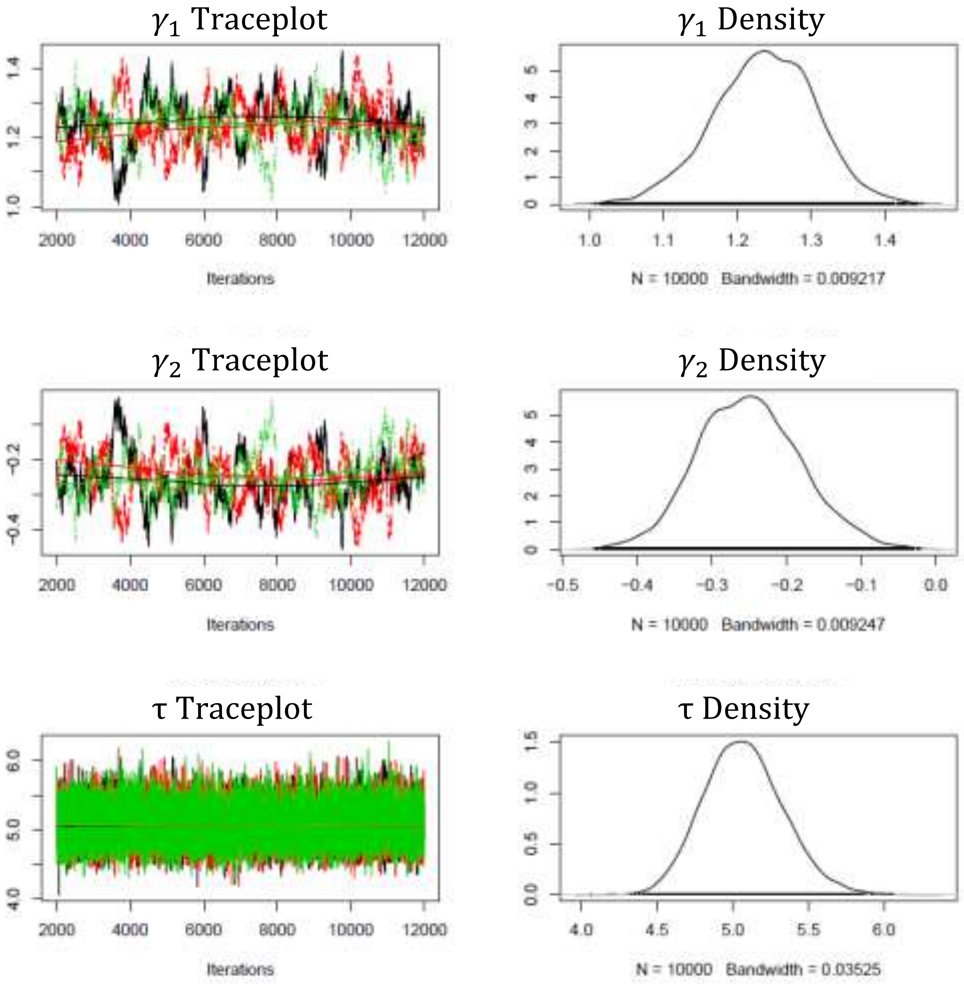


Table 3. Use rate AR(2) Parameter estimates

Parameter	Median	95% Credible interval
γ_1	1.249	$(-1.122\ ,\ 1.384)$
γ_2	-0.262	$(-0.397\ ,\ -0.135)$
τ	5.058	$(4.591\ ,\ 5.614)$

Predicting Behaviors of a New Wind Turbine

<u>Simulating from Posterior Predictive Distributions</u>

We consider a conditional approach and an unconditional approach. For the conditional approach we specify $t_{c_{22}}$ and

a) Draw λ_{22} and ϕ_{22} from the joint posterior distribution.
b) Draw a realization from an AR(2) process.
c) Simulate NHPP events until $t_{c_{22}}$ resulting in n_{22} events.
d) For each event generate downtimes $d_1, \ldots d_{n_{22}}$ using the equation in part 5.
e) Compute the MCF and accumulate
f) Repeat b) – e) B_2 times and average the results.
g) Obtain the 0.025, 0.5, and 0.975 quantiles of the predictive distribution, giving a point prediction and 95% prediction intervals for each point in time.

The unconditional approach is similar, but we would generate a new λ and ϕ each time.

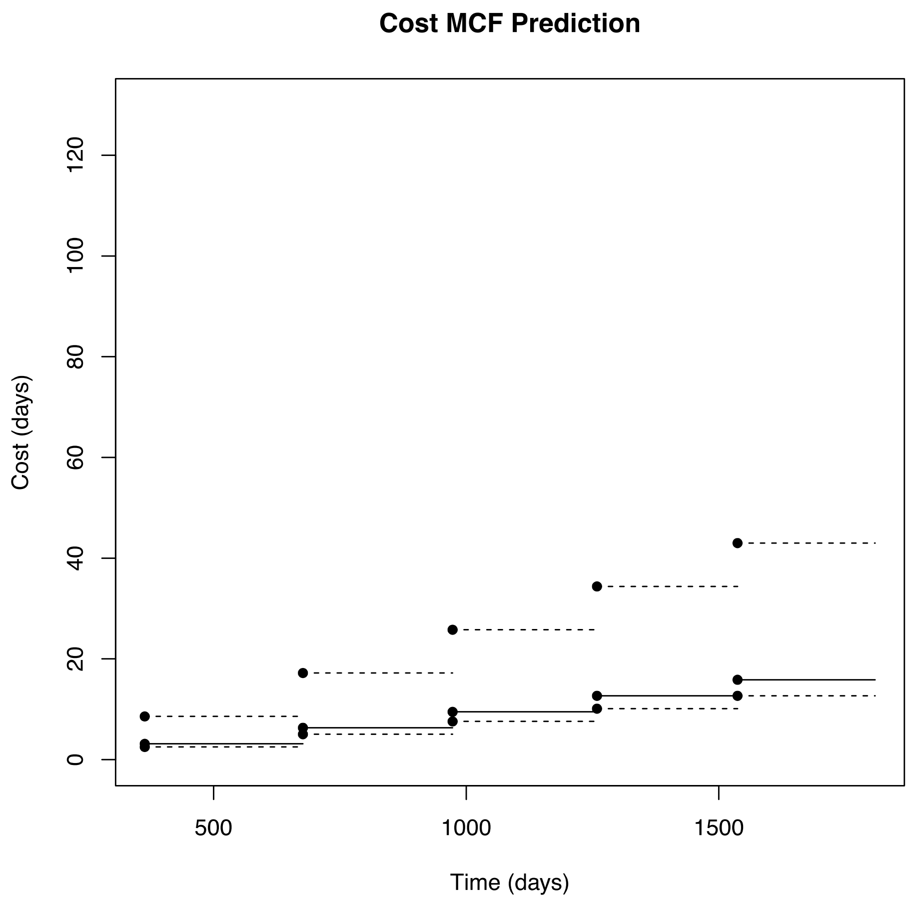
<u>Assumptions</u>

1. The relationship between use rates and costs in part 5 holds for Turbine 22.

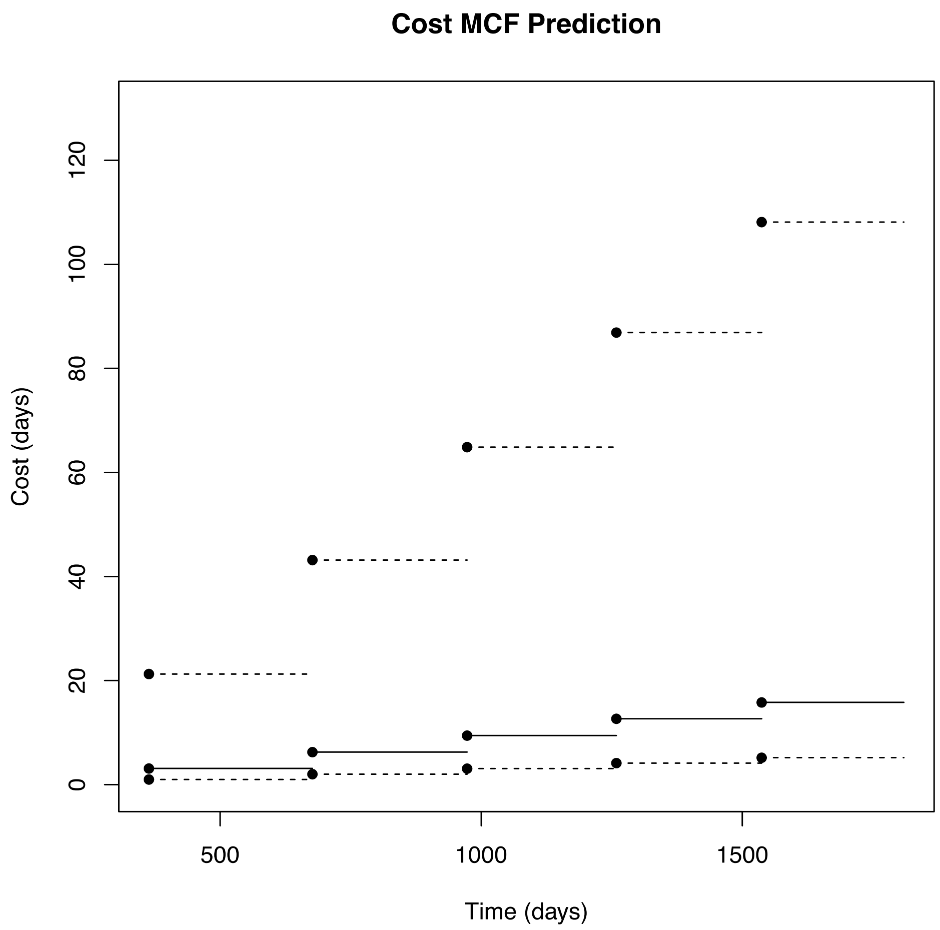
2. Recurrence rates are independent of cost parameters.

3. Turbine 22 comes from the same population of the originally observed wind turbines.

MCF Cost Results



Conditional predicted cost MCF with 95% prediction intervals.



Unconditional predicted cost MCF with 95% prediction intervals.

Conclusions

<u>A Compromise between Conditional and Unconditional Approaches</u>

Assumptions for cumulative cost prediction are

- Before we know anything about Turbine 22, deal with the cost MCF prediction unconditionally.
- Once operation begins, take data and update the prior.
- Prediction bounds decrease with increased prior information, as the prediction process becomes conditional on the prior information.

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Questions?