

# WIND TURBINE PROGNOSTIC HEALTH MANAGEMENT A STATISTICAL PREDICTIVE APPROACH

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# PRESENTER PROFILE

## Michael S. Czahor

- PhD Candidate
- IGERT Student on behalf of the NSF 2013-Current
- Wind Energy Science Engineering Policy and Statistics Co-Major
- Rowan University 2013 (Bachelors in Mathematics)
- Comcast Spectacor Intern (2012-2013)
- Major Professor: Dr. William Meeker

# PRESENTATION OUTLINE

- **Component Specific Reliability Research**
  - **Power Converter Reliability**
- **Proposed Model/Approach**
  - **Dynamic Covariates**
  - **Cumulative Damage Model**
- **Needs for Research**
  - **Concluding remarks**



PCS 6000 Wind

# RESEARCH PURPOSE

- Aiming to improve turbine reliability and availability
- Discover failure mode relationships
- Evaluate and predict the state of a wind turbine during its service life

# STEPS

- Obtain reliability data
- Data should include failures and non-failures
- Build a model to link environment with failure events
- Validate model
- Make predictions

# BENEFITS OF RESEARCH

- Mitigate the risks and consequences of failure
- Learn about failure modes
- Obtain accurate predictions of future failures



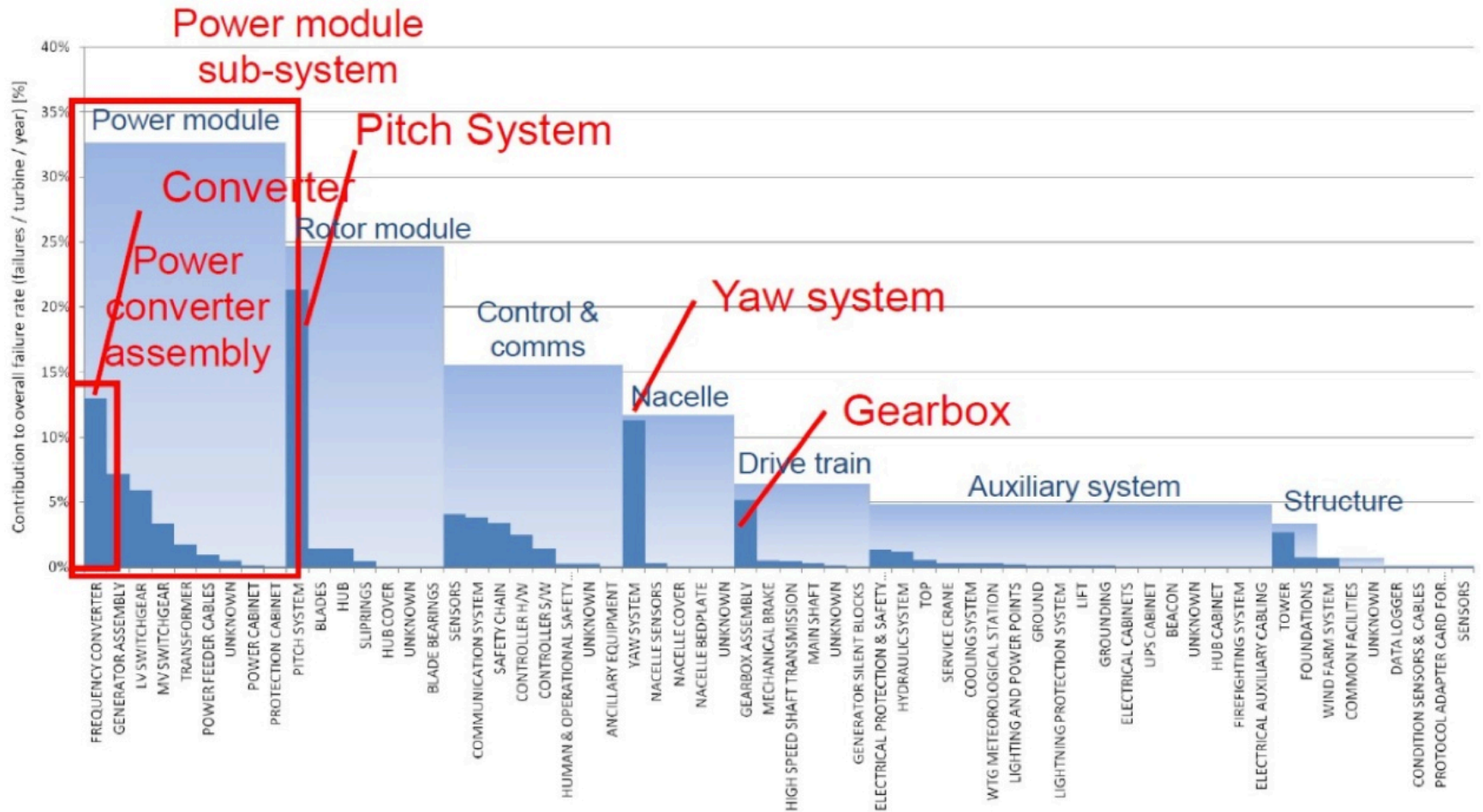
Swedish Offshore Wind Farm Maintenance: Picture from Siemens

# EXAMPLE TO FULFILL RESEARCH PURPOSE...

- Allow for use of advanced reliability analysis
- Ageing evidence
- Data expected to contain:
  - Module ID
  - Date of turbine installation
  - Location
  - Failure date or end-of-observation
  - Failure mode information
  - Covariate history

# FAILURES OF PITCH-CONTROLLED VARIABLE SPEED TURBINES

NORMALIZED FAILURE RATES :IMAGE FROM "RELIAWIND PROJECT" (2011)

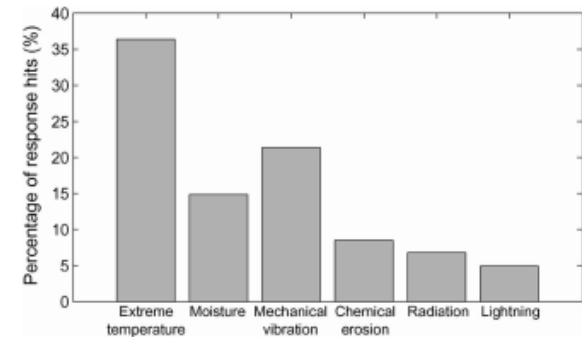
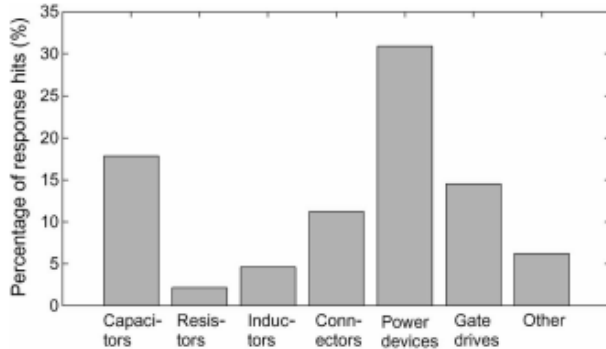




# COMMON FAILURE MODES OF POWER CONVERTERS (NOT NECESSARILY IN WIND TURBINES)

Chip-Related Failure Modes	Package-Related Failures
Electrical Overstress	Bond-wire lift-off
Latch-up and triggering of parasitic structures	Solder fatigue
Charge effects, ionic contamination or hot carrier injection	Degradation of thermal grease
Electro-migration, contact- and stress-induced migration	Fretting corrosion at pressure contacts
Thermal Activation	Tin whiskers

Failure modes of Power Converters



Survey results of weak points in power electronic systems and environmental variables that cause stress inside power electronic converters taken from Yang (2011)

# POWER CONVERTER ISSUES IN WIND TURBINES

FISCHER (2014)



## Condensation

- Causes
- Humidity
- Temperature
- Open Nacelle
- Effects
- High Thermal Inertia

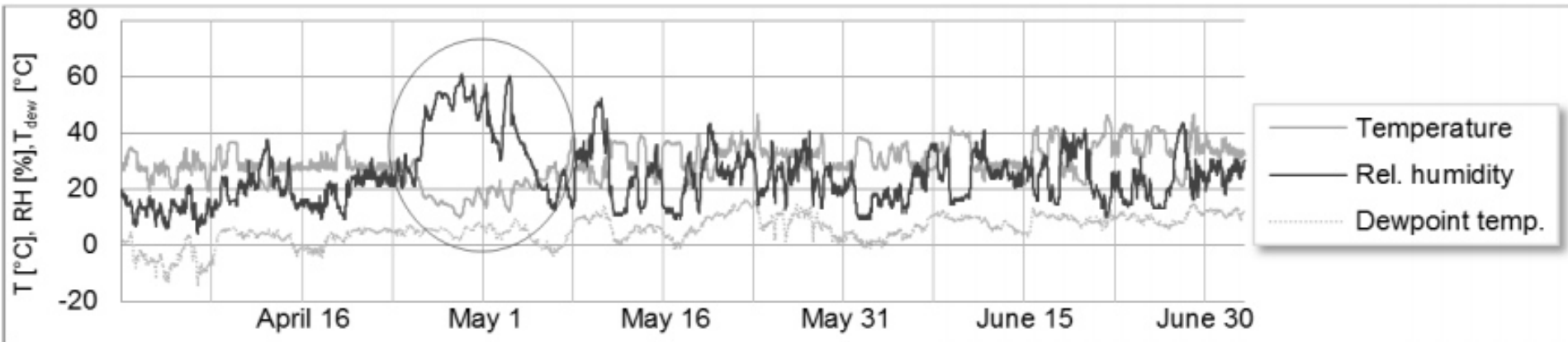
## Electrical Overstress

- Causes
- Lightning
- Effects
- Small Internal Cracks

## Flashover

- Causes
- Insects In Cabinet
- Effects
- Reduce Insulation Relevant Air Gaps

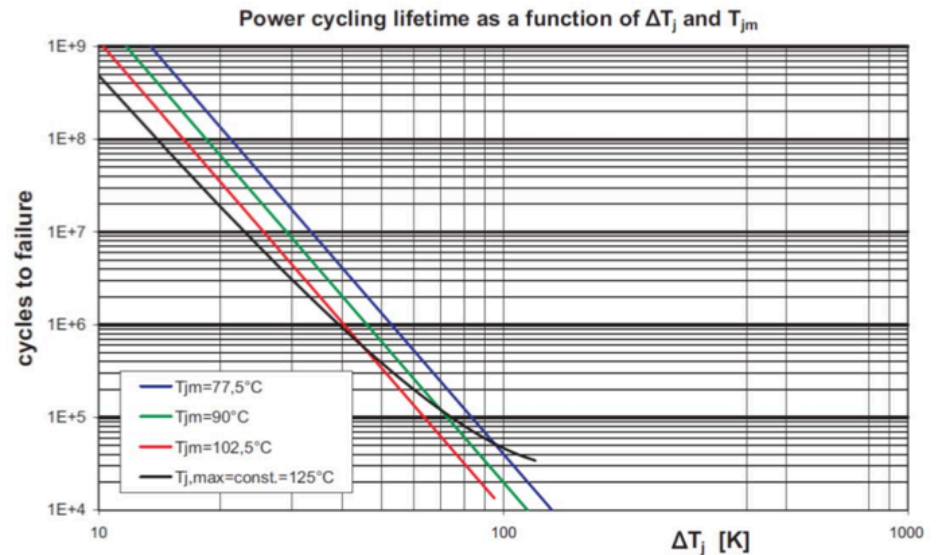
# CONDENSATION (DYNAMIC COVARIATE EXAMPLE)



Evidence of condensation during failure event from Fischer (2014)

# MODEL AND APPROACH: DYNAMIC COVARIATE DEFINITION

- Example within the realm of power converters  $\Delta T$  ,  $N$
- $\Delta T$ : temperature change with respect to time in the Insulated Bipolar Gate Transistor (IGBT) module at each cycle.
- $N$ : number of cycles over time
- Manufacturers will often provide information on the power-cycling capability of the IGBT modules.
- Plot from Wintrich (2011)



# MODEL AND APPROACH: USING DYNAMIC COVARIATES

- T: Time to failure
- $\delta$ : censoring indicator
  - $\delta = 1$  if a power converter fails
  - $\delta = 0$  if the power converter survives to the time of data analysis.
- $x_{ij}(t)$ : recorded value of covariate  $i$  for unit  $j$  at time  $t$
- Our proposed model allows for a vector covariate process
- Data being collected on individual power converter  $j$  will include  $\{t_j, \delta_j, x(t_j)\}$ .
- $\Delta_{\text{Temp}}$ : the difference between the minimum and maximum temperatures during thermal cycling over a specified time period
- $N_j$ : the number of cycles over the same specified time period for each power converter.

# MODEL AND APPROACH: CUMULATIVE DAMAGE MODEL

- Describe the effect that one or more dynamic covariates has on the failure time distribution.
- The latent (unobservable) cumulative damage  $u_j(t)$  for an individual power converter is modeled by:

$$u_j(t) = u_j[t; \beta_j, x_{ij}(t_j)] = \int_0^t \exp[\beta x(s)] ds.$$

- Relationship between cumulative damage and random failure time T

$$U = u(T) = \int_0^T \exp[\beta x(s)] ds .$$

- The cumulative distribution function (cdf) of failure time T given the entire covariate history is:

$$F(t; \beta, \theta_0) = \Pr(T \leq t) = \Pr\{U \leq u[t; \beta, x(t)]\}.$$

# MODEL AND APPROACH: CUMULATIVE DAMAGE MODEL CONT'D

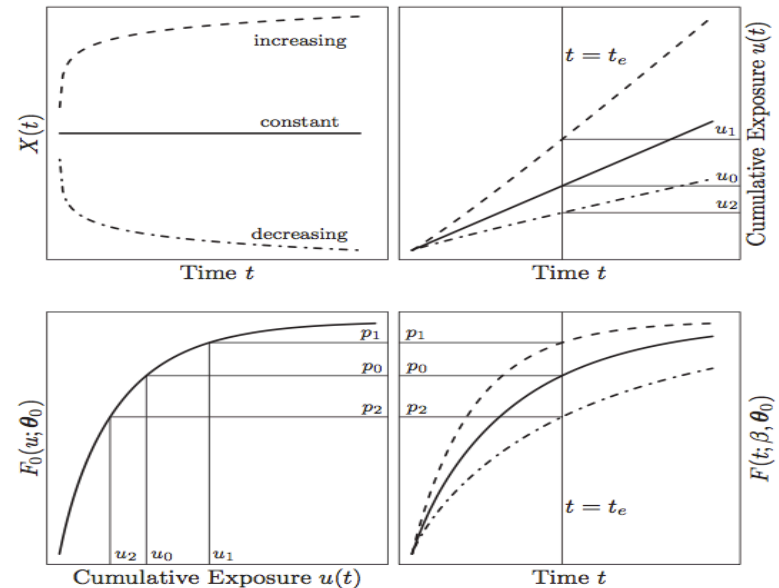
$$F_0\{u[t; \beta, x(t)]; \theta_0\}$$

- is the cdf of U

$$f(t; \beta, \theta_0) = \exp[\beta x(t)] f_0\{u[t; \beta, x(t)]; \theta_0\}$$

- is the pdf of failure time T

- Power converter failure time  $t$  will be dependent on the number and range of the thermal cycles within the IGBT module.



# MODEL AND APPROACH: PROPORTIONAL HAZARDS MODEL

## Proportional Hazards Model

- Biomedical Applications
- Uses no information from covariate history
- Would be appropriate if failures are caused by shocks, independent of unit age



# MODEL AND APPROACH: COVARIATE MODEL

## Covariate Model

- Needed to predict future damage accrual
- Build model and predict covariate process
- Multivariate times series model
- Possibly use a vector autoregressive moving average time series model

# MODEL AND APPROACH: PARAMETER ESTIMATION

- Establish covariate model (previous slide)
- Parameter estimation becomes two-step process
  - Obtain estimates of failure-time distribution parameters conditional on the set of observed covariate processes.
  - Obtain estimates for parameters in the covariate process.

$\theta_T = (\theta'_0, \beta)'$  → Failure-time distribution parameters

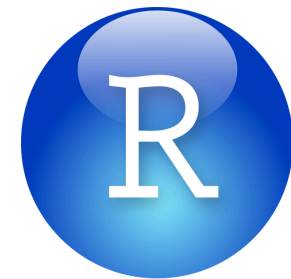
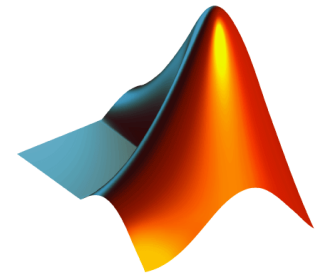
$\theta_X$  → Covariate model parameters

# MODEL AND APPROACH: FAILURE-TIME DISTRIBUTION PARAMETER ESTIMATION

$L(\theta_T | FT \text{ Data, Covariate History})$

$$\prod_{i=1}^n \{ \exp[\beta x_i(t_i)] f_0(u[t_i; \beta, x_i(t_i)]; \theta_0) \}^{\delta_i} * \{ 1 - F_0(u[t_i; \beta, x_i(t_i)]; \theta_0) \}^{1-\delta_i}$$

- Write programs in R or Matlab to find
  - Parameter estimates
  - Standard errors
- To obtain fitted cumulative damage values
- Plug in the ML estimates of each parameter



# MODEL AND APPROACH: COVARIATE PROCESS PARAMETER ESTIMATION

$$L(\theta_X | \text{Covariate History}) =$$

$$\prod_{i=1}^n \int_{w_i} \left\{ \prod_{t_{ij} \leq t_i} f_{NOR}[x_i(t_{ij}) - \eta - Z_i(t_{ij})w_i; \sigma^2] \right\} * f_{BVN}(w_i; \Sigma_w) dw_i$$

- Statistical software: R
  - lme package
  - Compute  $\theta$  for a given correlation structure

# MODEL AND APPROACH: PREDICTION PROCEDURE SUMMARY

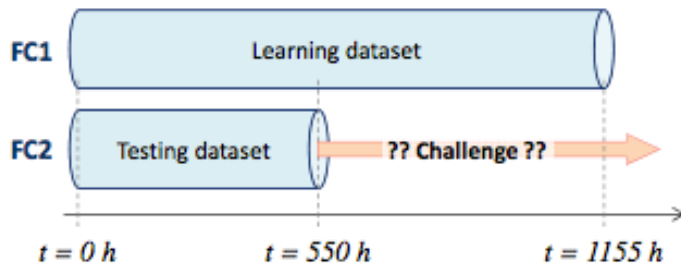
- Adapt theory and methods used in Hong and Meeker (2013)
- Estimate remaining useful life distributions
- Strong covariate information → Reduce width of prediction intervals
- Predictions for an entire wind farm
  - Predictions for individual units
  - Cumulative number of failures → Maintainers/Manufacturers

# NEEDS FOR RESEARCH: MODEL ASSESSMENT

- Good fit to the data does not indicate predictive ability
- Assess predictive ability of cumulative damage models

## Cross Validation

- Measure predictive performance
- Easy to overfit by including too many parameters
- “Training set”



### FC1 (Without Ripple)

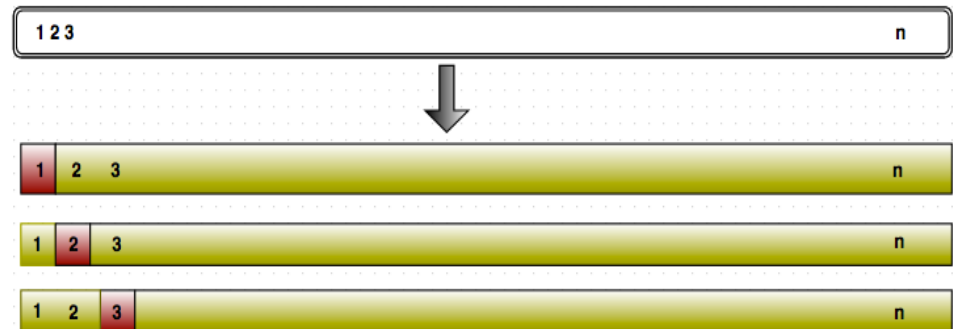
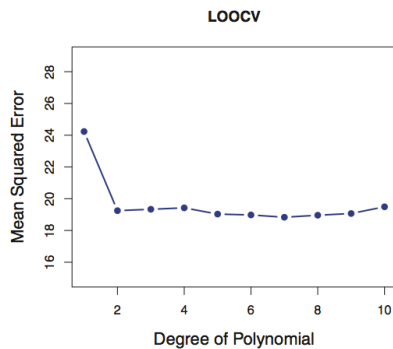
Characterizations (Polarization + EIS)	@ $t = 0; 48; 185; 348; 515; 658; 823; 991\text{ h}$
1. EIS performed before polarization	@ $J = 0.70\text{ A/cm}^2$
2. Polarization curve	Ramp: from $0\text{ A/cm}^2$ to $1\text{ A/cm}^2$ of $1000\text{ s}$
3. EIS performed after polarization	@ $J = \{0.70; 0.45; 0.20\}\text{ A/cm}^2$

### FC2 (With Ripple)

Characterizations (Polarization + EIS)	@ $t = 0; 35; 182; 343; 515; 666; 830; 1016\text{ h}$
1. Polarization curve	Ramp: from $0\text{ A/cm}^2$ to $1\text{ A/cm}^2$ of $1000\text{ s}$
2. EIS performed after polarization	@ $J = \{0.70; 0.45; 0.20\}\text{ A/cm}^2$

# NEEDS FOR RESEARCH: LEAVE-ONE-OUT CROSS VALIDATION (LOOCV)

1. Assume there are  $n$  independent observations  $y_1, \dots, y_n$
2. Form a test set from observation  $i$ , i.e. leave this observation out and fit the model using the remaining data
3. Compute the predicted residual (or error) as  $e_j^* = y_j - \hat{y}_j$
4. Repeat steps 2 and 3 for all  $i$
5. Compute Mean Squared Error (MSE) from  $e_1^*, e_2^*, e_3^*, \dots, e_n^*$  (in this context, called Cross-Validation (CV) error)



# CONCLUSIONS

## SUMMER 2015 PROJECT/INTERNSHIP

### R&D cluster on reliable power electronics for wind turbines

#### Project focus and objectives:

- ↪ Improving reliability and availability of frequency converters in wind turbines
- ↪ Root-cause analysis, countermeasures for existing and future turbines
- ↪ System behaviour in dynamic operation
- ↪ Condition monitoring for electronics
- ↪ Fault-tolerant generator/converter concepts

#### Project partners:

- ↪ Fraunhofer IWES, Fraunhofer ISIT
- ↪ 4 universities
- ↪ 22 industry partners

**Duration:** 2013 – 2016 **Budget:** 8 M€



#### Research partners:



#### Industry partners:



Internship Summary (Work schedule: May 16<sup>th</sup>, 2015-August 27<sup>th</sup>, 2015)



# QUESTIONS



# REFERENCES

- [1] Fischer, Katharina, T. Stalin, H. Ramberg, J. Wenske, G. Wetter, R. Karlsson, and T. Thiringer (2014). "Field-Experience Based Root-Cause Analysis of Power-Converter Failure in Wind Turbines." *IEEE Transactions on Power Electronics* PP.99
- [2] Wilkinson, Michael (2011). *Methodology and Results of the Reliawind Field Study*. Tech. Garrad Hassan.
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