Wind Turbine Gearbox Remaining Useful Lifetime Prediction and Early Failure Detection

Siemens PLM - Engineering & Consulting Services, Belgium
R. Dekkers, W. Vandermeulen, P. Bonnet, W. Hendricx
Winergy, Germany
E. Hidding, M. Uhlending, D. Endemann, N. Hoevelbrinks

Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

SIEMENS
Ingenuity for life

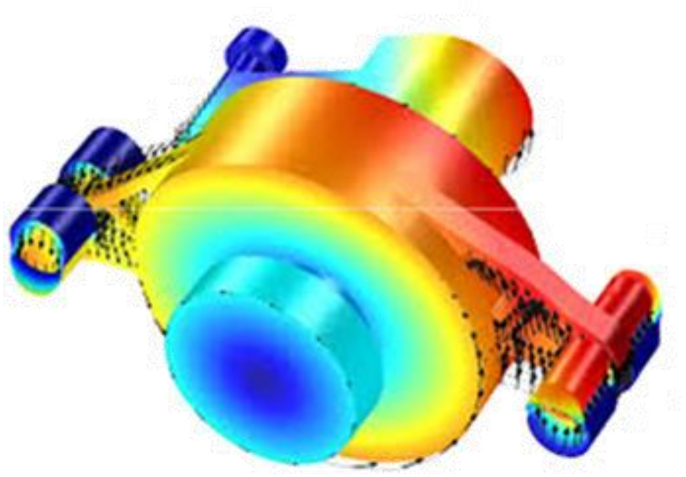
- **Introduction**
- Input data
- Remaining Useful Lifetime
  - Model creation & validation
  - Load accumulation
  - Lifetime prediction
- Early Failure Detection
  - Neural Network
- Conclusion

Introduction

SIEMENS
Ingenuity for life

Wind farm maintenance is exceptionally challenging

- Shorter lifetime than expected 20 years
- Critical issue: gearbox



Need for Predictability of the maintenance costs of each turbine

- **R**emaining **U**seful **L**ifetime (RUL) of each gearbox in the wind farm
- Early Failure Detection tool
  => Maintenance and budget planning

Reliable historical data

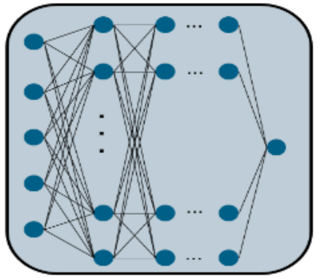
- Logged turbine controller data: SCADA (Supervisory Control and Data Acquisition)
- **To be able to calculate the gearbox RUL based on <u>only SCADA data</u> is a huge advantage!**

"Proof of Concept" collaboration project

- Utility/wind farm operator, Siemens PLM and Winergy

Dual Technical approach

SIEMENS
Ingenuity for life

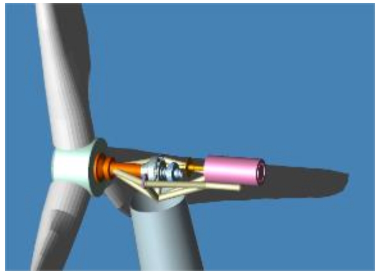


- SCADA Monitoring data – **78 Wind Turbines**
  72 channels (wind speed, rpm, gearbox temp, faults, …)
- Service history

→ Data stored over **4 years**

Data gathered and organized in **MindSphere**

MindSphere Asset Manager



Neural Network (NN)

Training Neural Network

Failure prediction and detection

Turbine Model (SWT)

Digital Twin: Model creation and correlation

SCADA load cases

Remaining lifetime of gears and bearings for each wind turbine

Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

SIEMENS
Ingenuity for life

- Introduction
- **Input data**
- Remaining Useful Lifetime
  - Model creation & validation
  - Load accumulation
  - Lifetime prediction
- Early Failure Detection
  - Neural Network
- Conclusion

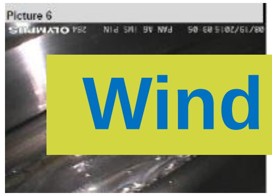
Input data

SIEMENS
Ingenuity for life

SCADA Database

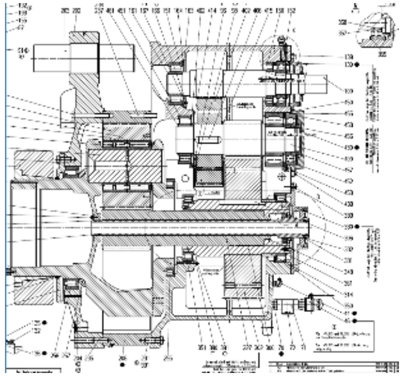
SCADA name	Description
AngleBlade1	Angle of blade 1
AngleBlade2	Angle of blade 2
AngleBlade3	Anlge of blade 3
SpeedGenCCU	Generator speed
SpeedGenPLC	Generator speed
AngleNacelle	Nacelle Angle
OperatingState	Operating state of the turbine
PowerGen	Generated power
SpeedRot	Rotor speed
TempGbxBrg1	Gearbox temperature bearing 1
TempGbx	Gearbox temperature
TempGbxBrg2	Gearbox temperature bearing 2
TorqueGen	Generator torque
SpeedWind	Wind speed
PrePressHssBrake	Hydraulic brake pressure
TempAmbient	Ambient temperature
TempNacelle	Nacelle temperature
TowerAccMag	Tower acceleration

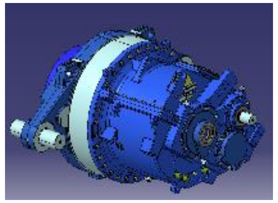
Repair history



Wind Farm Operator

Detailed gearbox information





Winergy

Dedicated measurements on 1 turbine

Siemens PLM

Input data

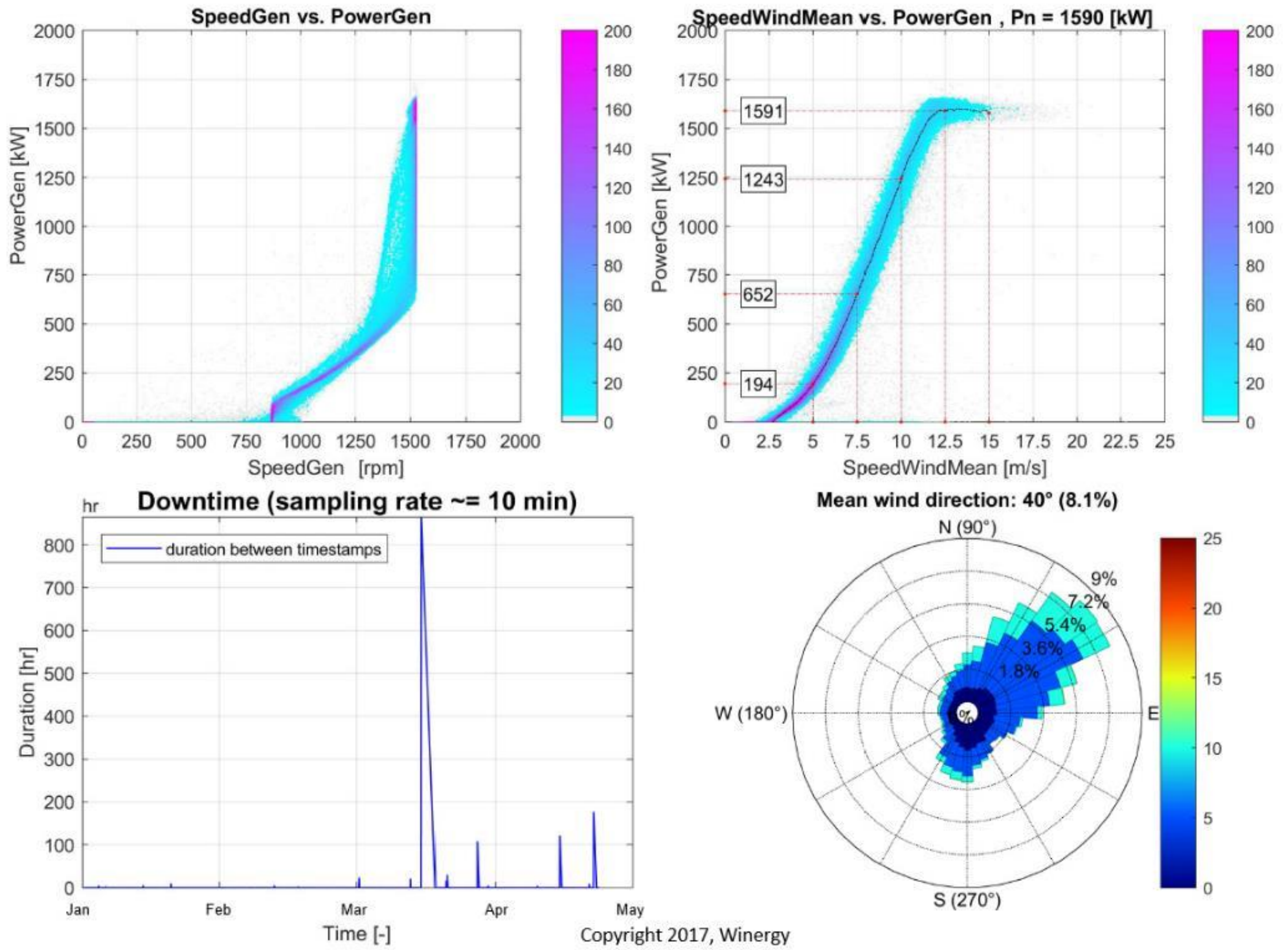
SIEMENS
Ingenuity for life

SCADA data

10 minute data points
- Average
- Minimum
- Maximum
- Standard deviation

Event & fault logging
- Braking
- Pitching
- Errors
- ….

SCADA name	Description
AngleBlade1	Angle of blade 1
AngleBlade2	Angle of blade 2
AngleBlade3	Anlge of blade 3
SpeedGenCCU	Generator speed
SpeedGenPLC	Generator speed
AngleNacelle	Nacelle Angle
OperatingState	Operating state of the turbine
PowerGen	Generated power
SpeedRot	Rotor speed
TempGbxBrg1	Gearbox temperature bearing 1
TempGbx	Gearbox temperature
TempGbxBrg2	Gearbox temperature bearing 2
TorqueGen	Generator torque
SpeedWind	Wind speed
PrePressHssBrake	Hydraulic brake pressure
TempAmbient	Ambient temperature
TempNacelle	Nacelle temperature
TowerAccMag	Tower acceleration



Copyright 2017, Winergy

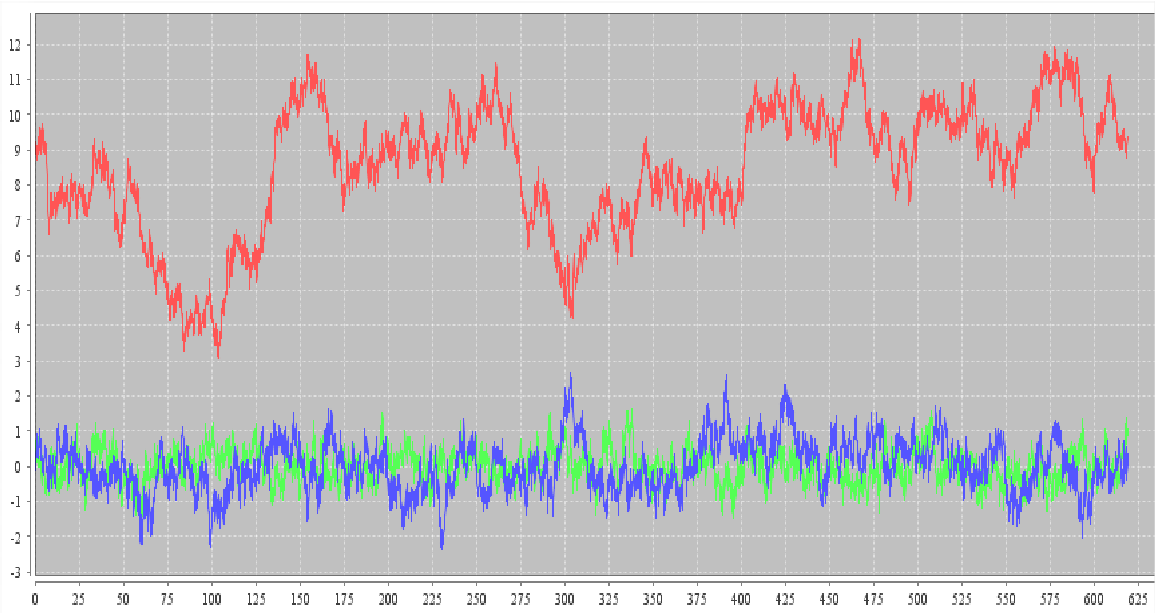
Input data

SIEMENS
Ingenuity for life

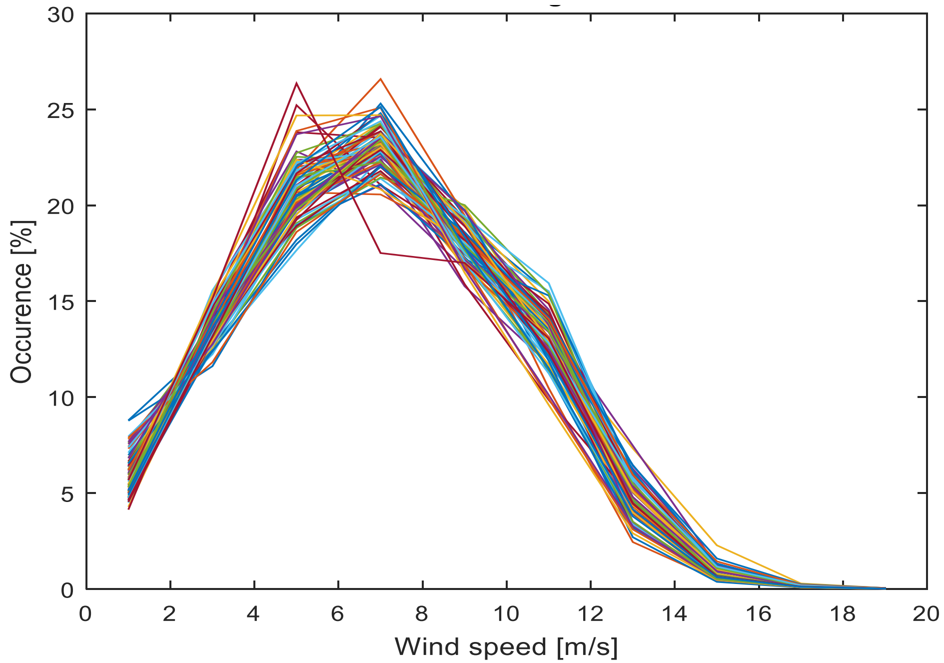
SCADA - Creation of Wind time series

- Based upon SCADA 10-minute data samples: wind speed average, standard deviation minimum and maximum
- Classification in wind classes as function of **wind speed** and **turbulence**

Simulated wind times series



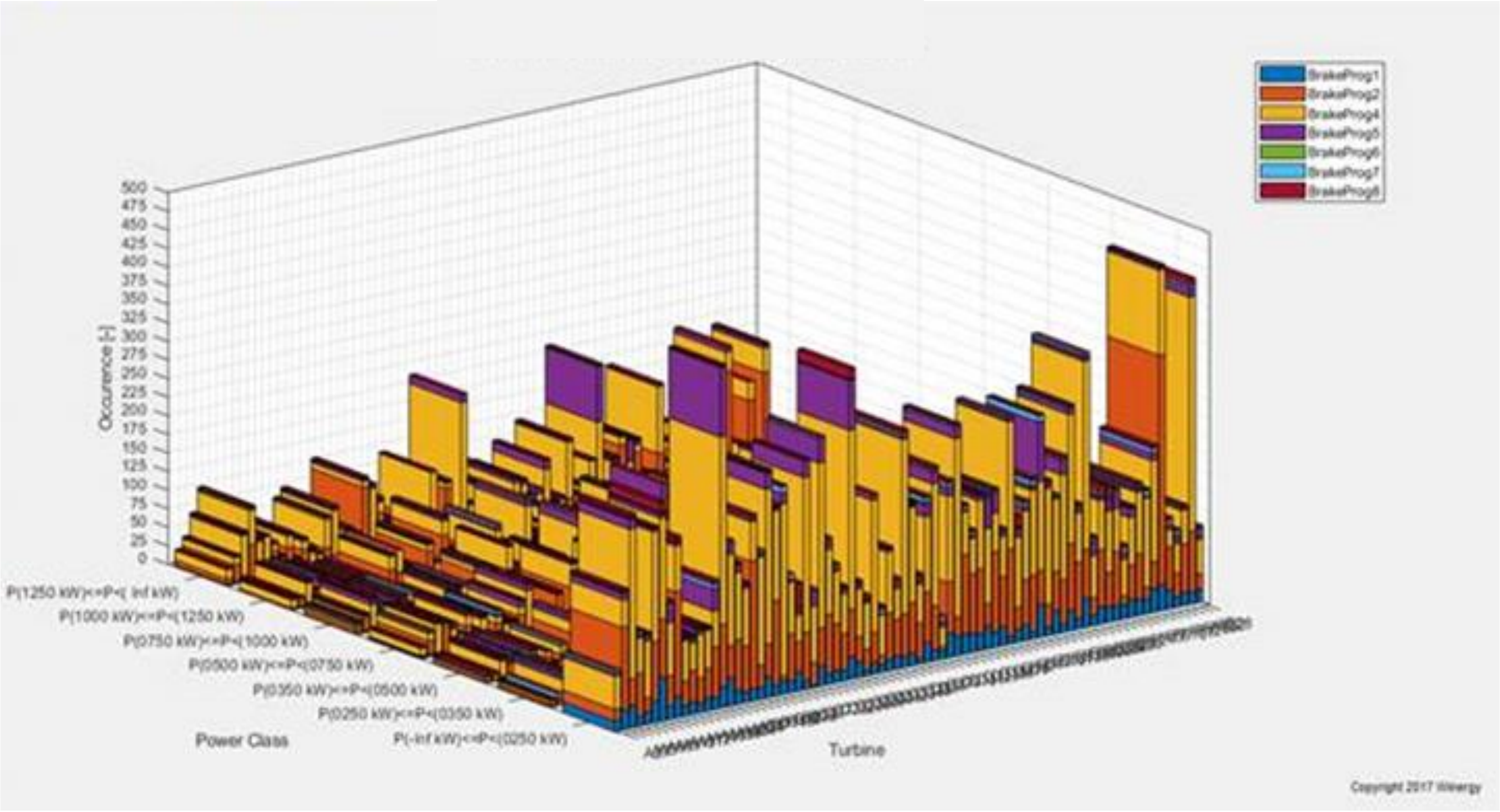
6m/s wind speed histogram (low turbulence)



Input data

SCADA - Brake events

- 8 brake types: depends of blade pitching, mechanical braking & magnetic braking contributions
- For all turbines during a 4 year period: Cumulative number of occurrences of each braking type



Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

SIEMENS
Ingenuity for life

- Introduction
- Input data
- Remaining Useful Lifetime
  - **Model creation & validation**
  - Load accumulation
  - Lifetime prediction
- Early Failure Detection
  - Neural Network
- Conclusion

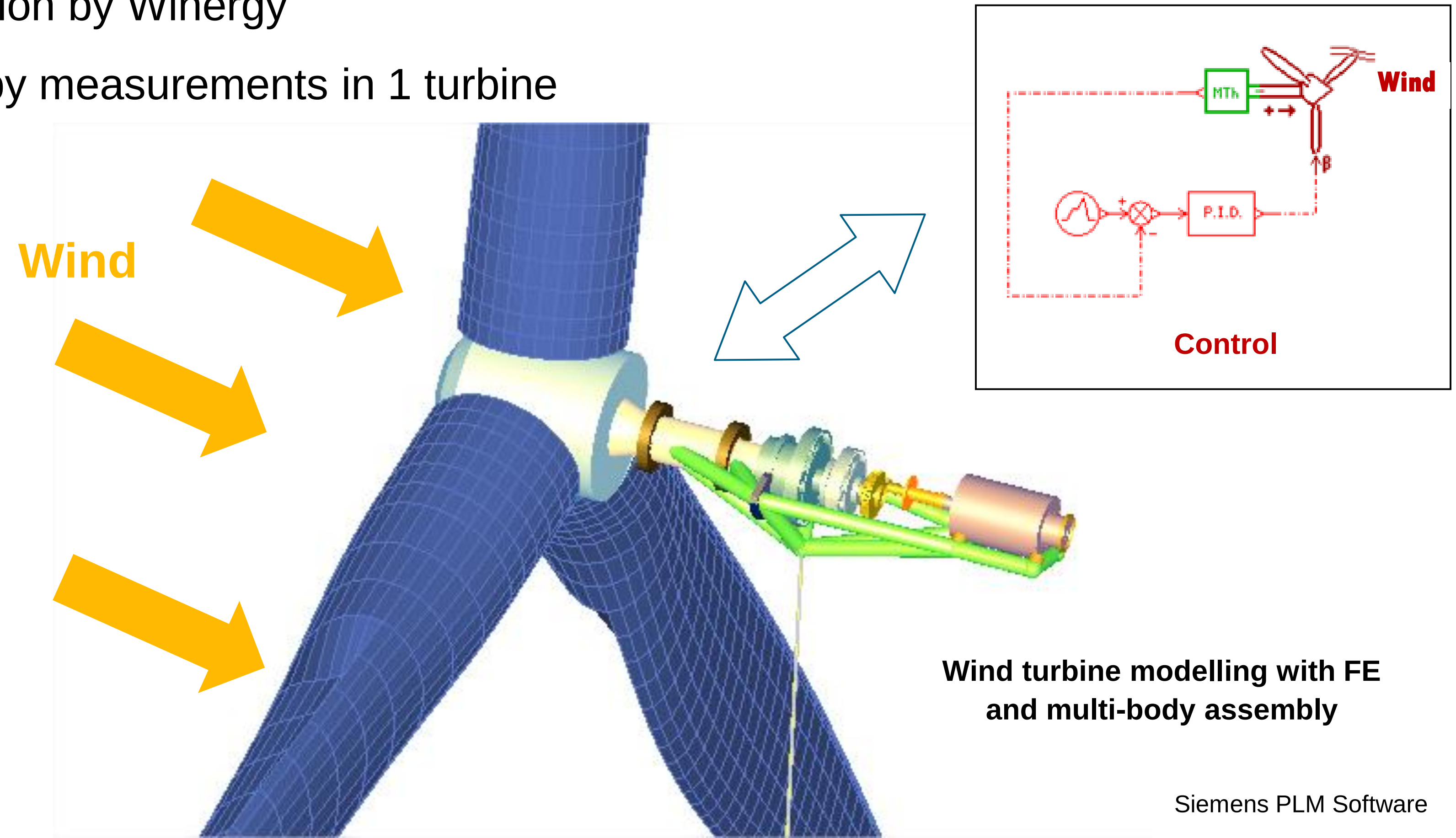
Model creation

Wind turbine modelling

- *LMS Samcef for Wind Turbine* (SWT) combined kinematic-dynamic model of the entire turbine
- Detailed gearbox model information by Winergy
- *Reverse Engineering* of turbine by measurements in 1 turbine
- Driving force: Wind time series

Model includes

- Blades and the Hub
- Main shaft
- Winergy gearbox
- Speed Coupling shaft
- Generator
- Bedplate
- Tower
- Pitch controller



Wind turbine modelling with FE and multi-body assembly

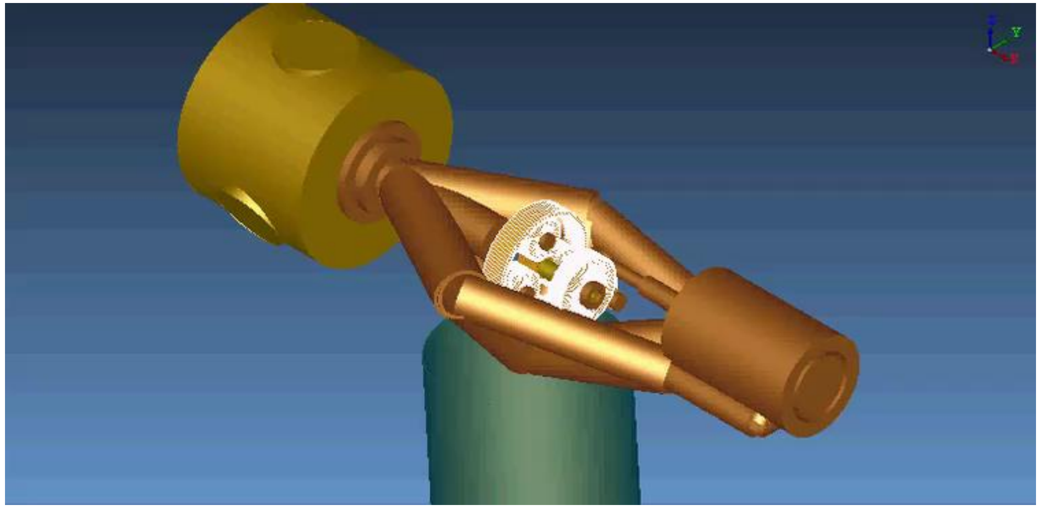
Model creation

SIEMENS
Ingenuity for life

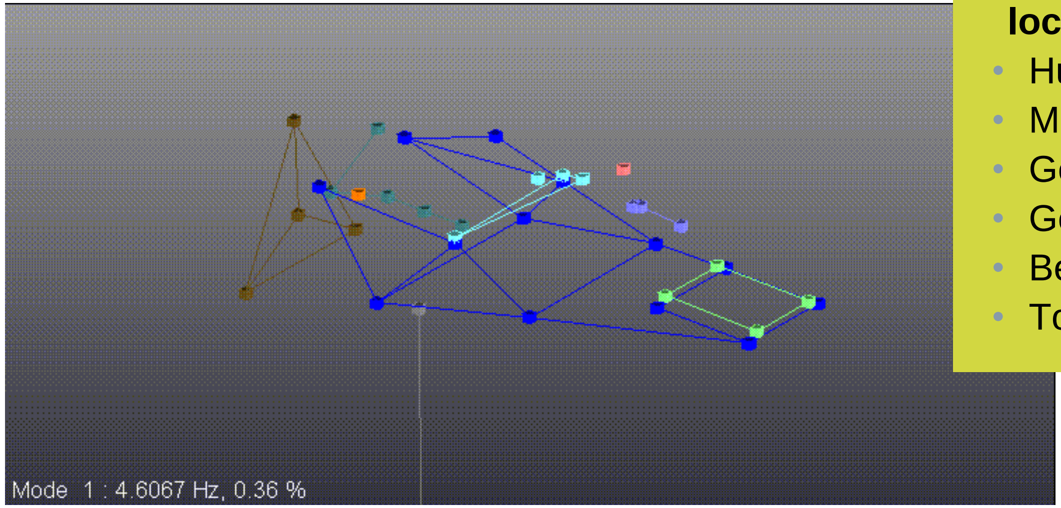
Model validation measurements in 1 turbine

- Aim: Identification of the global turbine dynamics (resonances)
- Vibration response measurements by artificial excitation (hammer impact)
- Updating of SWT model (without wind!) based upon measurements

Simulated nacelle yawing mode



Measured nacelle yawing mode



Measurement locations (120 DOF)
- Hub
- Main shaft
- Gearbox
- Generator
- Bedplate
- Tower

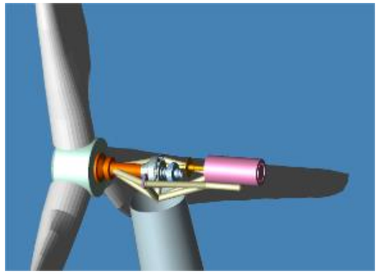
Model creation

SIEMENS
Ingenuity for life

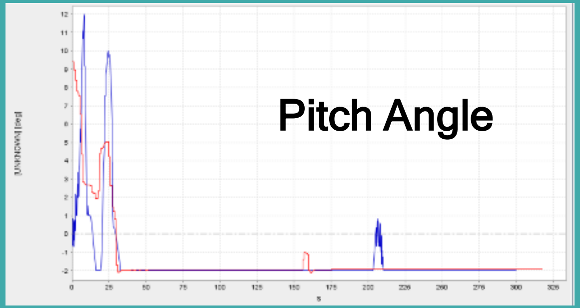
Response validation measurements: Semi steady-state wind excitation

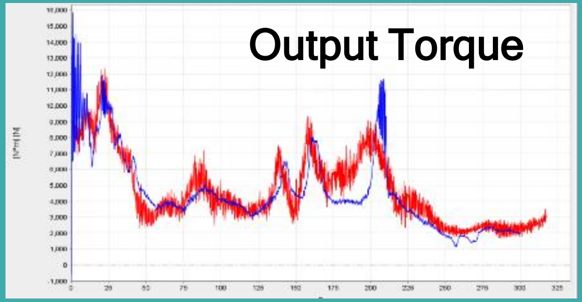
Model input

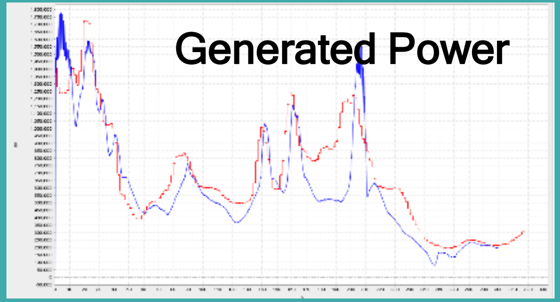
Measured wind speed time series



Model output







Measurement
SWT Modelling

Model creation

Response validation measurements: Transient operation

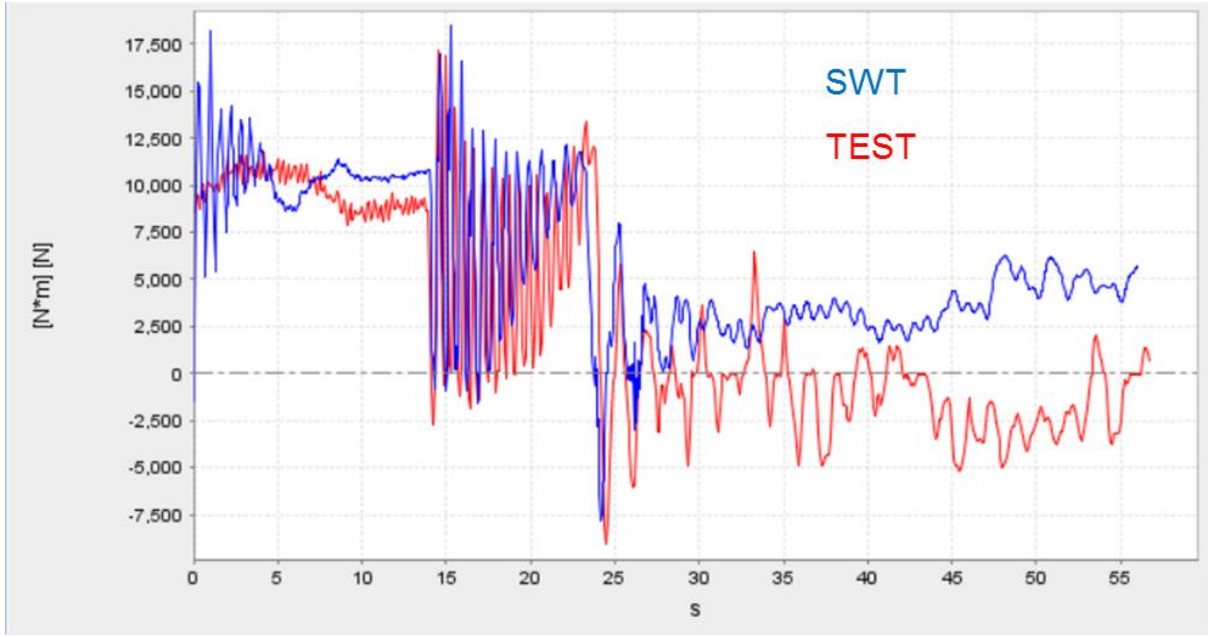
- Aim: Verification of gearbox loads during transients (e.g. stopping and starting, yawing, …)

<u>Operational response correlation</u>

- **Operational measurements on 1 turbine**
- **Update of the parameters (e.g. control settings, damping, rotational dynamics, …) to fit the response**

Operational Validated model ✓

Torque at LSS during braking event



Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

SIEMENS
Ingenuity for life

- Introduction
- Input data
- Remaining Useful Lifetime
  - Model creation & validation
  - **Load accumulation**
  - Lifetime prediction
- Early Failure Detection
  - Neural Network
- Conclusion

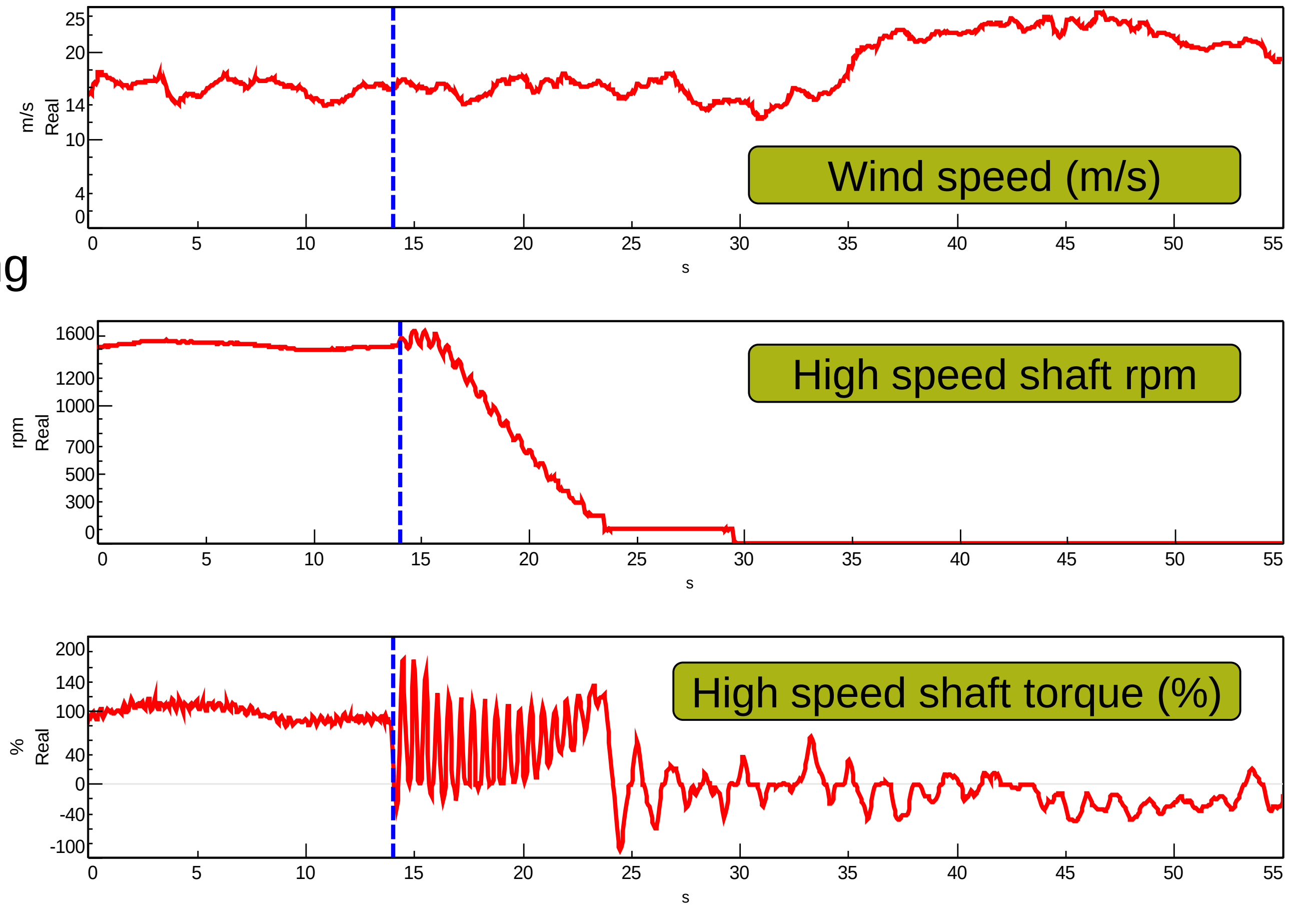
Load accumulation

SIEMENS
Ingenuity for life

Conversion of brake events to gearbox loads

- Loads measurements in 1 turbine
- Instrumented gearbox: RPM and torque
- Application of several braking events
    - Most frequently observed in SCADA logging
    - Most severe (E-Stop)

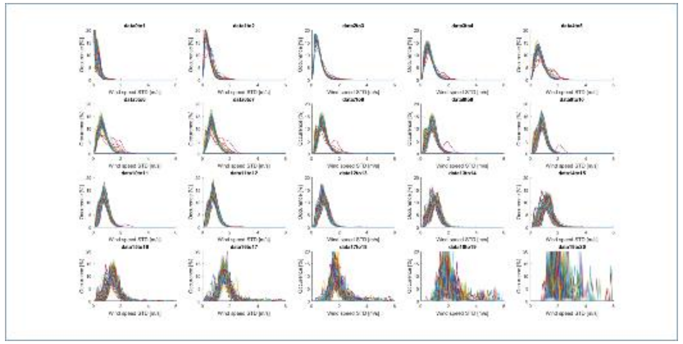
Gearbox loads during braking event

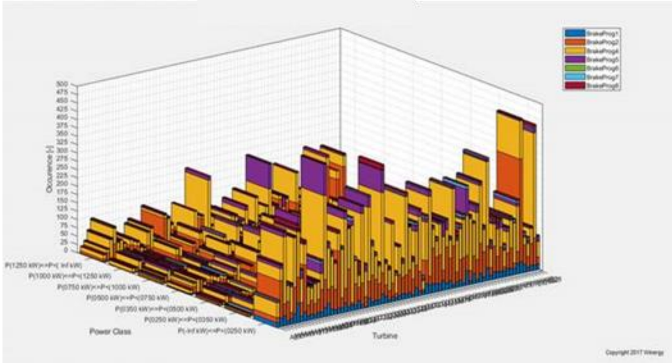


Load accumulation

Loads cascading: from SCADA to bearing & gear teeth forces

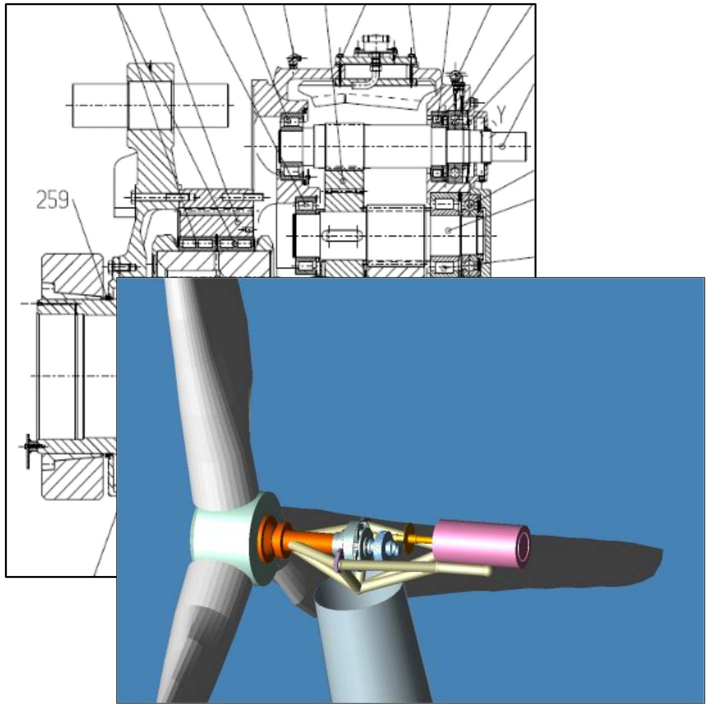
Clearly defined operating conditions





+

Validated turbine model with detailed gearbox



=

Loads for all components for all operating conditions

- BRAKE_4_timeseries.csv
- BRAKE_8_timeseries.csv
- LMS_Occurences.xlsx
- LoadCase3_timeseries.csv
- LoadCase4_timeseries.csv
- LoadCase5_timeseries.csv
- LoadCase6_timeseries.csv
- LoadCase7_timeseries.csv
- LoadCase8_timeseries.csv
- LoadCase9_timeseries.csv
- LoadCase10_timeseries.csv
- LoadCase11_timeseries.csv
- LoadCase12_timeseries.csv
- LoadCase13_timeseries.csv
- LoadCase14_timeseries.csv
- LoadCase15_timeseries.csv
- LoadCase16_timeseries.csv
- LoadCase17_timeseries.csv
- LoadCase18_timeseries.csv
- LoadCase19_timeseries.csv
- LoadCase20_timeseries.csv

Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

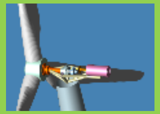
SIEMENS
Ingenuity for life

- Introduction
- Input data
- Remaining Useful Lifetime
  - Model creation & validation
  - Load accumulation
  - **Lifetime prediction**
- Early Failure Detection
  - Neural Network
- Conclusion

Lifetime prediction

SIEMENS
Ingenuity for life

Remaining Lifetime Process

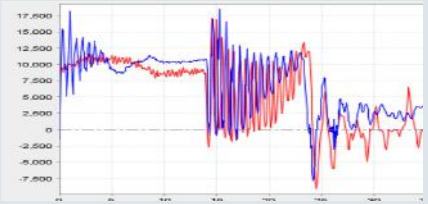


Correlated Digital Twin

Digital Twin: Samcef for Wind Turbine Correlation with TEST

Experimental Modal Analysis

Operational Measurements



- Emergency stops creating high torques in shafts
- Normal operation, low and high wind speeds
- Blade pitching
- Generated Power/torque

Load cases from SCADA

Correlated SWT model loaded with turbulent wind and brake activation

Load for each bearing and gear pair

Load case occurrence in each wind turbine

Accumulated damage in each component for each wind turbine

Remaining Useful Lifetime for each wind turbine at component level

Lifetime prediction

SIEMENS
Ingenuity for life

Loads
Individual load spectrum derived from individual load case occurances

Load capacity
Material data, manufacturing data, design information, field data, supplier information

Digital Twin

The "DigitalTwin" is an developed algorithm which collects and prepares the whole input data. The model is created <u>individually for each gearbox</u> and contains the connection between load and load capacity.

Output = f(Duration, Torque, Speed, Temperatur,…)

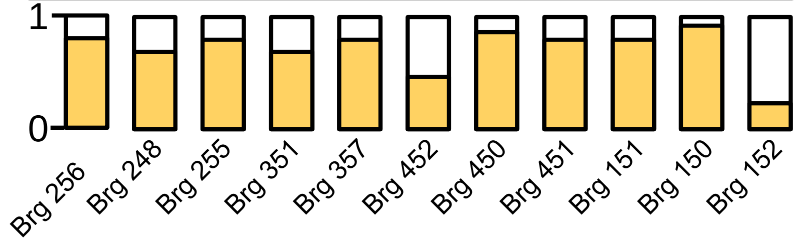
Output

Gearing

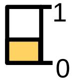
Generals

- ConsumedLoadCycles
- ConsumedLifeTime
- ExpectedLifeTime.
- RemainingYears
- …

Bearings



<u>Remaining Useful Life (RUL)</u>



*0 = New component
*1 = Lifetime reached (theoretical failure)

Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

SIEMENS
Ingenuity for life

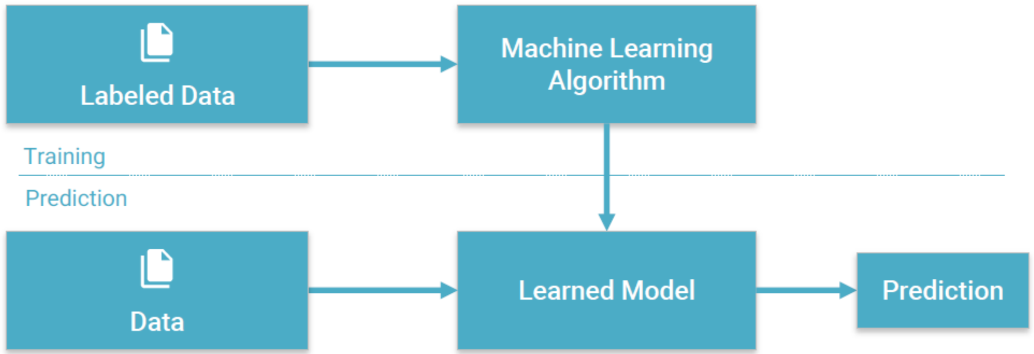
- Introduction
- Input data
- Remaining Useful Lifetime
  - Model creation & validation
  - Load accumulation
  - Lifetime prediction
- Early Failure Detection
  - **Neural Network**
- Conclusion

Early Failure Detection: Neural Network

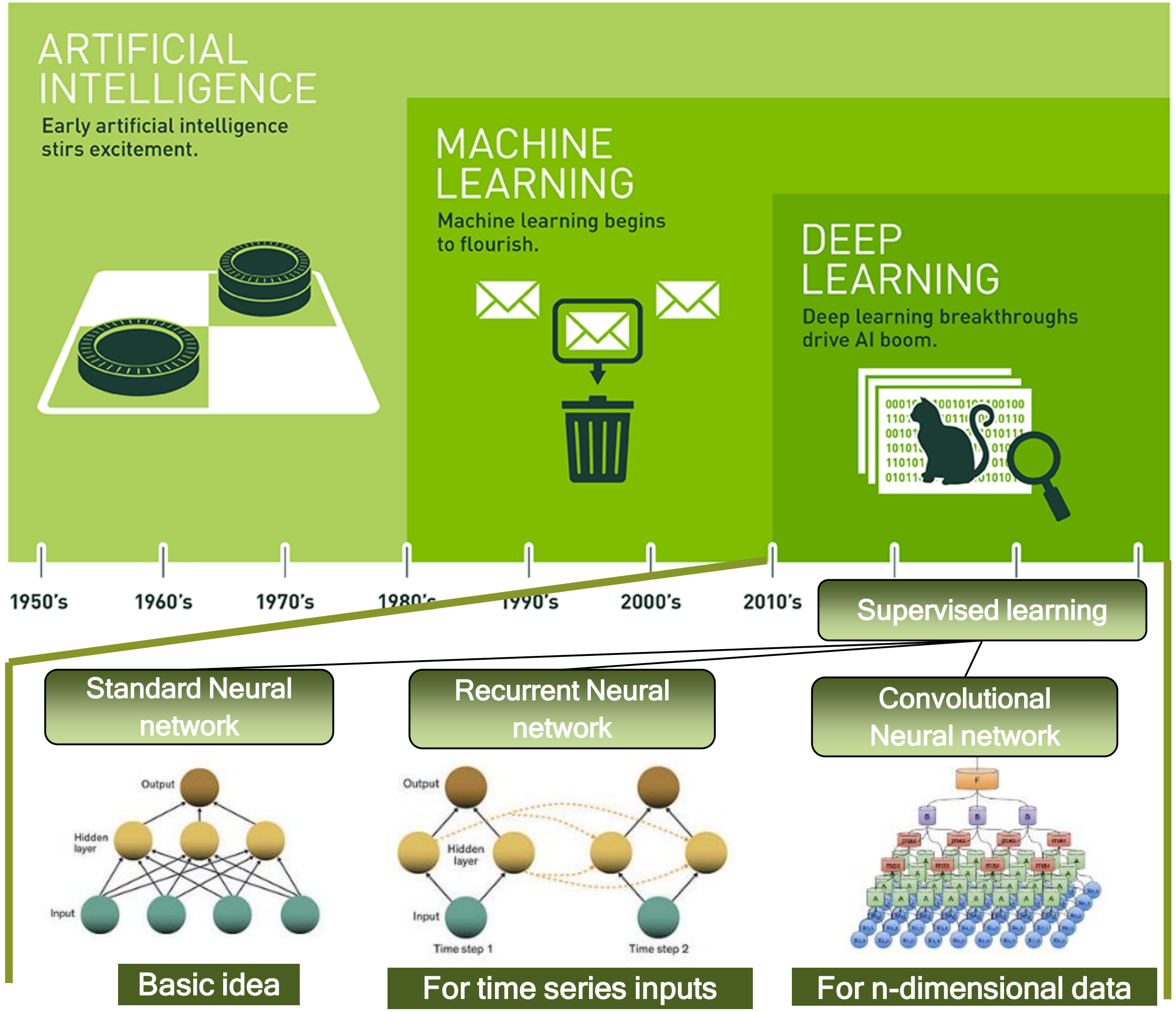
SIEMENS
Ingenuity for life

Recurrent Neural Network

Machine Learning is a type of Artificial Intelligence that provides computers with the ability to learn without being explicitly programmed.



Provides various techniques that can learn from and make predictions on data



Early Failure Detection: Neural Network

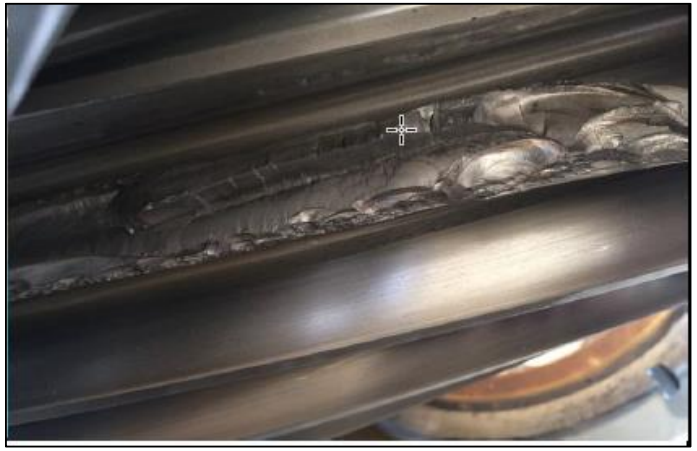
SIEMENS
Ingenuity for life

Service history

Only a small amount of gearbox failures is observed

- 6 turbines were repaired in the available data timeframe
- Repairs are linked to **gear** and **bearing damages** (cracks)

Turbine	Date	What	Remark
A	19/8/2015	Notice	Broken tooth on the intermediate pinion found
	24/8/2015	Repair	Intermediate speed shaft
	26/8/2015	Repair	Intermediate assembly + three bearing replacement
B	1/4/2015	Repair	Intermediate speed shaft
	13/4/2015	Notice	Broken teeth on the intermediate gear found
C	30/07/2015	Notice	Gen allingment, all OK
	1/5/2017	Repair	Intermediate speed shaft
	3/19/2017	Notice	Cracks in IMS gen side bearing + planetary gears damages
D	1/4/2015	Repair	Intermediate speed shaft
	8/4/2015	Notice	Broken tooth on the intermediate gear
E	4/14/2015	Notice	Cracks in bearings generator side and spalling on the planetary bearings
	18/05/2015	Repair	Intermediate speed shaft
	29/09/2017	Notice	All OK
F	13/10/2014	Repair	Intermediate speed shaft



Early Failure Detection: Neural Network

SIEMENS
Ingenuity for life

SCADA signals representative for potential gearbox damage

Available SCADA signals

SCADA name	Description
AngleBlade1	Angle of blade 1
AngleBlade2	Angle of blade 2
AngleBlade3	Anlge of blade 3
SpeedGenCCU	Generator speed
SpeedGenPLC	Generator speed
AngleNacelle	Nacelle Angle
OperatingState	Operating state of the turbine
PowerGen	Generated power
SpeedRot	Rotor speed
TempGbxBrg1	Gearbox temperature bearing 1
TempGbx	Gearbox temperature
TempGbxBrg2	Gearbox temperature bearing 2
TorqueGen	Generator torque
SpeedWind	Wind speed
PrePressHssBrake	Hydraulic brake pressure
TempAmbient	Ambient temperature
TempNacelle	Nacelle temperature
TowerAccMag	Tower acceleration

Typical (bearing) monitoring signals (e.g. vibration) are not available !

Assumption: Gearbox temperatures are most likely to be influenced by gearbox bearing failures:

- TempGbxBrg1
- TempGbx
- TempGbxBrg2

Early Failure Detection: Neural Network

SIEMENS
Ingenuity for life

Gearbox temperature prediction

Inputs

Generator Power

Ambient Temperature

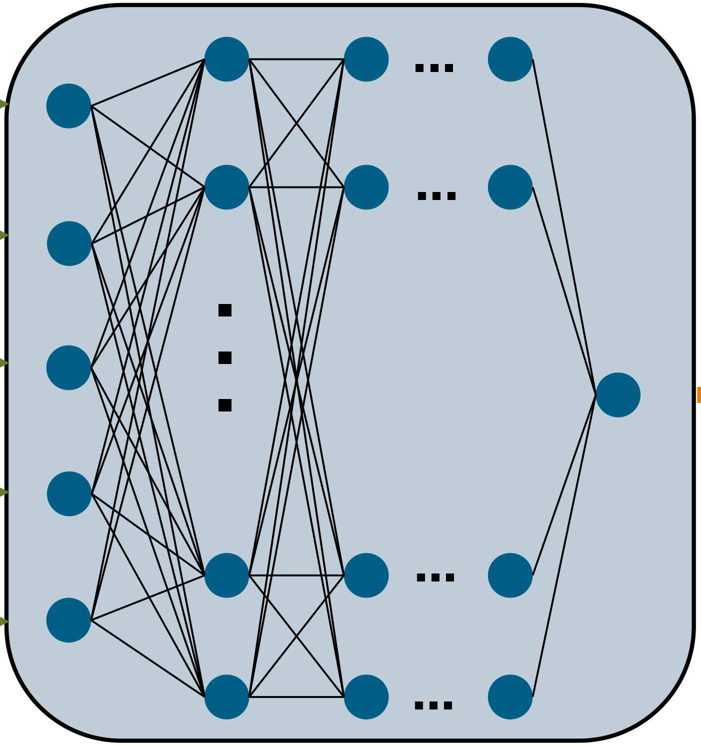
Rotation Speed

Generator Torque

Wind Speed

Considered failures will not affect these input channels

Recurrent Neural Network - RNN



Output

Gearbox Temperature

Most likely channel to observe the considered failures

GRU element: adds a recurrent element to the network = memory capability, possibility to influence the next result with the previous result

Early Failure Detection: Neural Network

SIEMENS

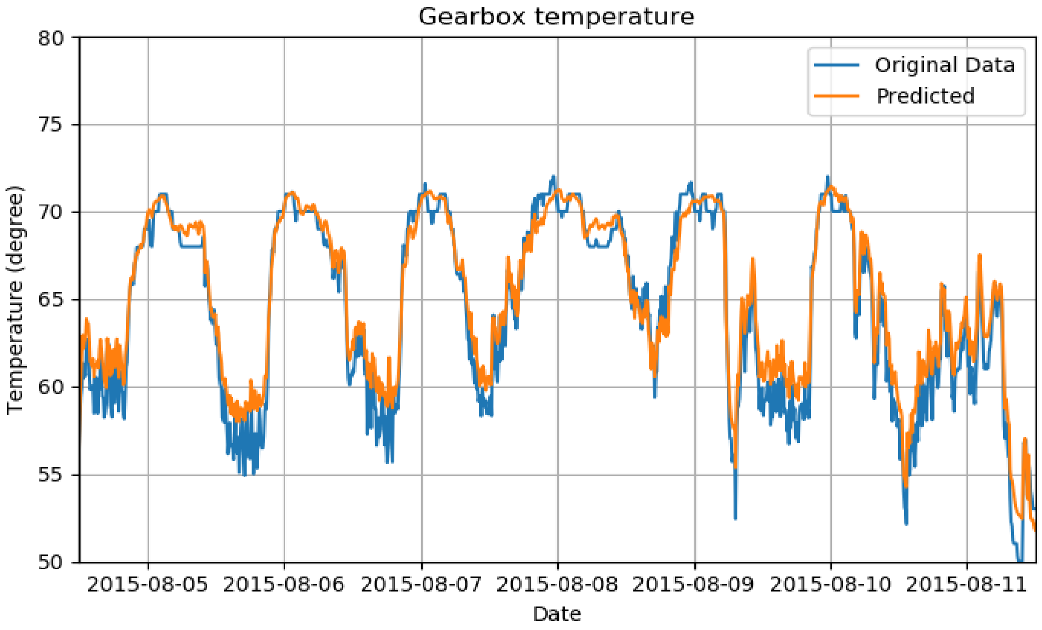
1. **Create a Neural Network that can predict gearbox temperatures from inputs that are not influenced by failures**

   Input → **NN** → $T_{Gearbox}$

2. **Train the neural network with data when no failure is present**
   - The networks learns how a healthy turbine reacts

3. **Feed the complete dataset to the network**
   - Prediction of gearbox temperature is an indicator for failure
   - Accurate = Healthy state
   - Drifts and inaccuracies = Non-healthy state

   Input → **NN** → Prediction $T^*_{Gearbox}$ **?** ↔ Measurement $T_{Gearbox}$



Accurate Temperature prediction

Failure in cooling system would change temperature response

Difference between predicted and actual temperature will detect this in early stage (slow drift)

Early Failure Detection: Neural Network

SIEMENS
Ingenuity for life

Lessons learned

- Neural Networks can be used to estimate accurately gearbox performance KPIs
- In the available SCADA database, the amount of gearbox related data was very limited
  - Vibration sensor data was not available
  - Only 3 temperature sensors were installed
- The Neural Network need to be trained with “good” and “faulty” data
  - The Winergy gearboxes are too good! The amount of fault occurrences is statistically not significant.

⇨ **The NN technology works**

⇨ **The added value depends of the amount & quality of the input data**

Wind Turbine Gearbox Remaining Lifetime Prediction and Early Failure Detection

SIEMENS
Ingenuity for life

- Introduction
- Input data
- Remaining Useful Lifetime
  - Model creation & validation
  - Load accumulation
  - Lifetime prediction
- Early Failure Detection
  - Neural Network
- **Conclusion**

Conclusions

SIEMENS
Ingenuity for life

Remaining Useful Lifetime (RUL)

- Proof of concept: It is possible to predict the Remaining Useful Lifetime (RUL)!
- **High quality input data** is an absolute requirement
  - Complete and consistent SCADA data
  - Detailed information of the monitored component: Gearbox
    - Design, material & component details
    - Design rules – Load assumptions
    - Knowledge of component suppliers
  - Turbine dynamic model
    - Info provided by turbine OEM
      OR
    - Reverse engineering based upon measurements and public domain data

Early failure detection

- Proof of concept: NN can be used to predict gearbox condition parameters
- A large database of **‘*failures*’** is required to train the network