

MODELING THE DYNAMIC BEHAVIOR OF WIND FARM POWER GENERATION

BUILDING UPON SCADA SYSTEM ANALYSIS





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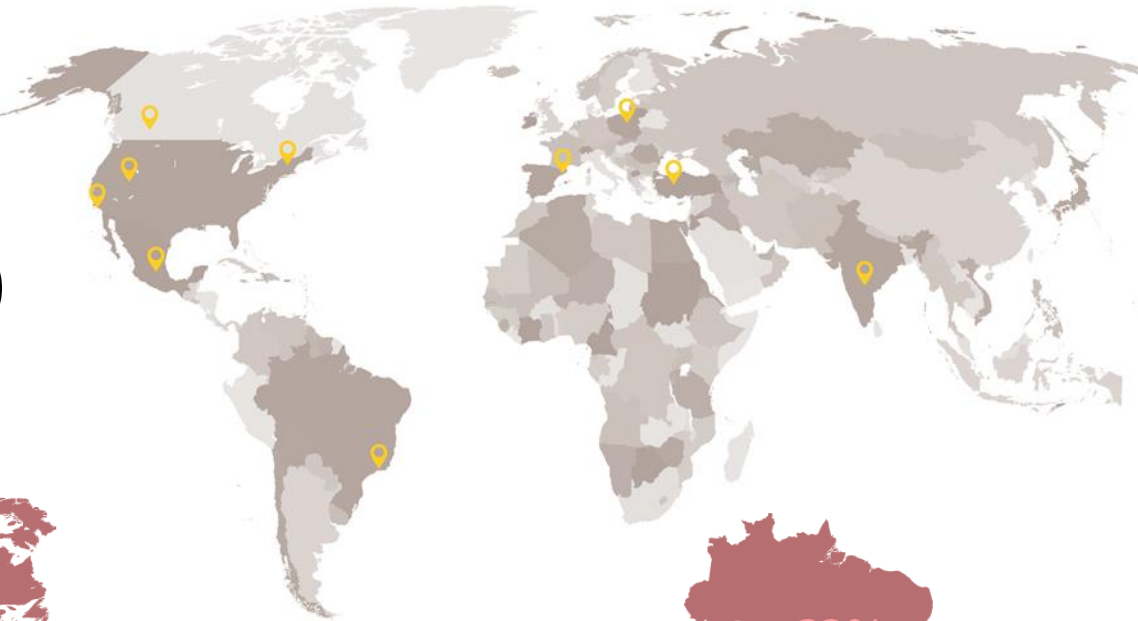
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Director of OpenWind

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President and CTO

Assessed resource and energy for over **half** of all **India** wind projects over the last two years.

125,000

Megawatts (MW)
Assessed



30+

Years of Experience



85%

of our staff is comprised of engineers, meteorologists and environmental specialists.

80+

Number of Countries
Where We Worked

50%

Approximately 50% of US wind projects financed in 2015 used AWST Energy Production Reports.

43 GW

We provide renewable energy forecasting services to over 43 gigawatts (GW) of capacity.

33%

Consulted to about a third of all Brazil wind projects that came online over the last two years

Presentation Overview

MODELING THE DYNAMIC BEHAVIOR OF WIND FARM POWER GENERATION

- Project Scope
- Overview of operational plant data
- Atmospheric modeling
- Time series energy modeling
- Conclusion: key accomplishments, challenges, next steps

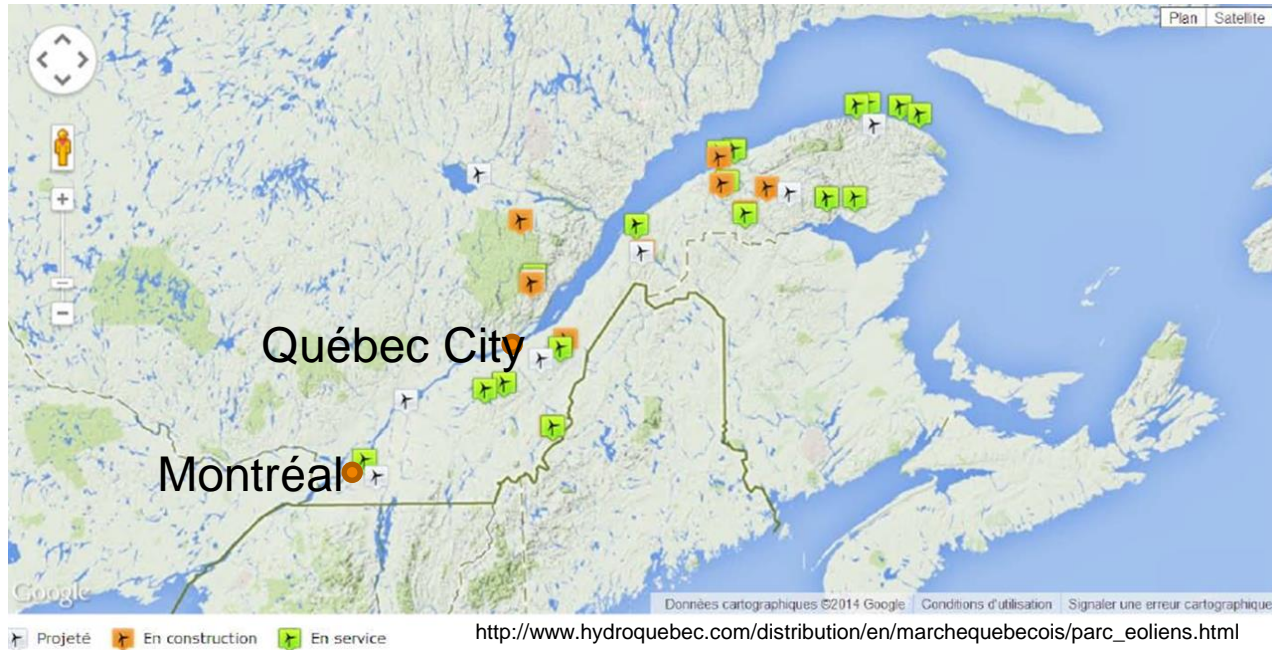
Wind Power Time Series

TYPICAL APPLICATIONS

- Wind Resource Assessment: Annual Energy Production (AEP) estimates based on time-varying atmospheric conditions and plant losses
- Operational performance: analysis of historical wind plant generation
- Environmental curtailments
- Grid integration studies

Wind farms in Québec, Canada (under contract with Hydro-Québec Distribution)

39 WIND FARMS : 18 IN OPERATION + 21 PLANNED OR IN CONSTRUCTION



Methodology for Time Series Energy Modeling

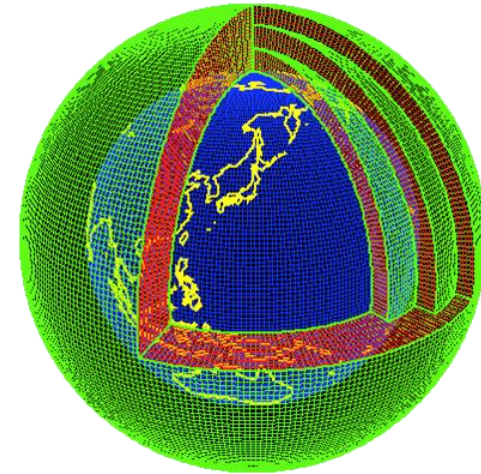
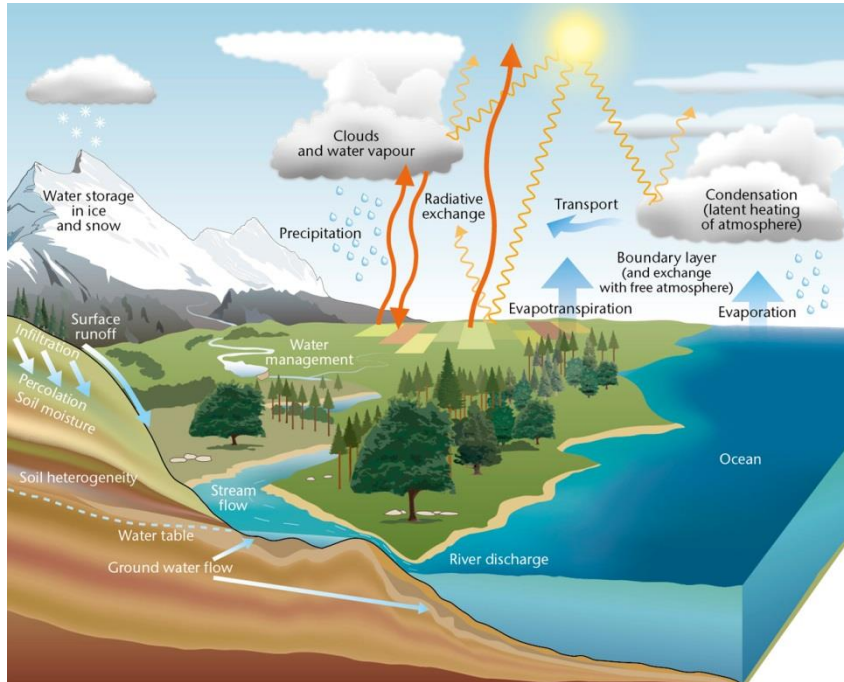
Step 1

Atmospheric Modeling
(e.g. WRF)

- Wind (u,v,w),
- Temperature,
- Pressure,
- Air Density,
- Relative Humidity,
- etc.

Atmospheric Modeling

MESOSCALE NUMERICAL WEATHER PREDICTION (NWP) MODEL

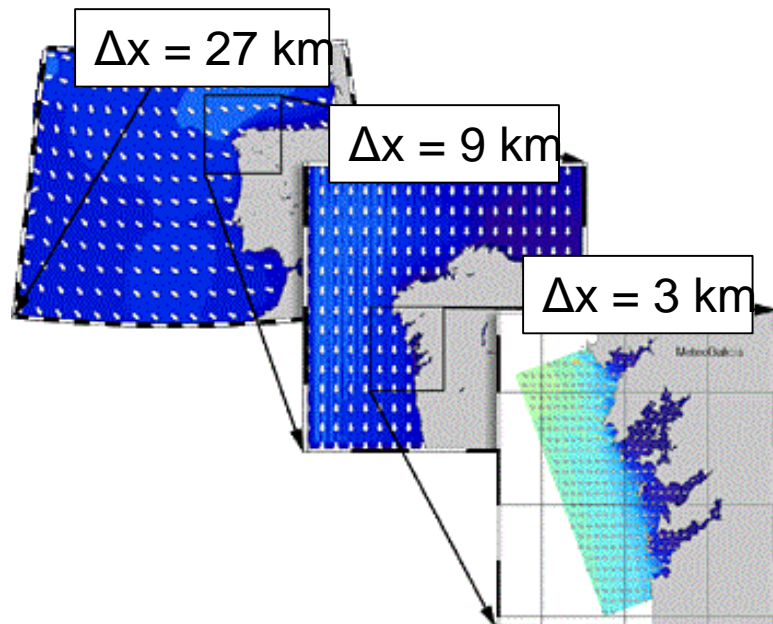


<http://www.jma.go.jp/jma/jma-eng/jma-center/nwp/nwp-top.htm>

Numerical Weather Prediction Modeling

WEATHER RESEARCH AND FORECASTING (WRF)

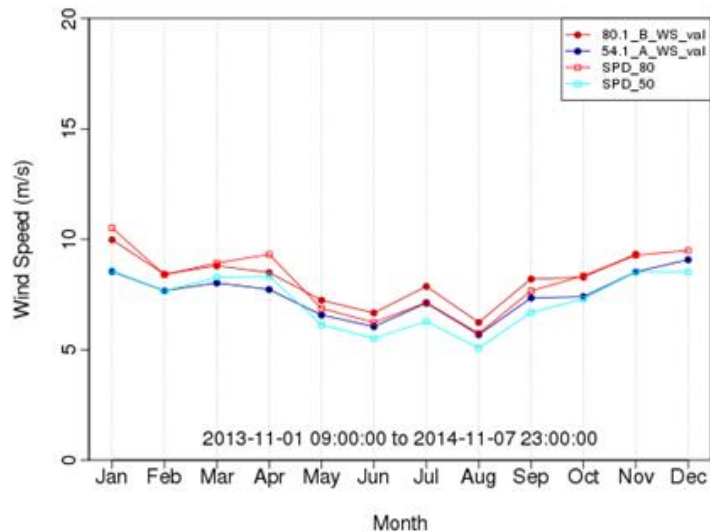
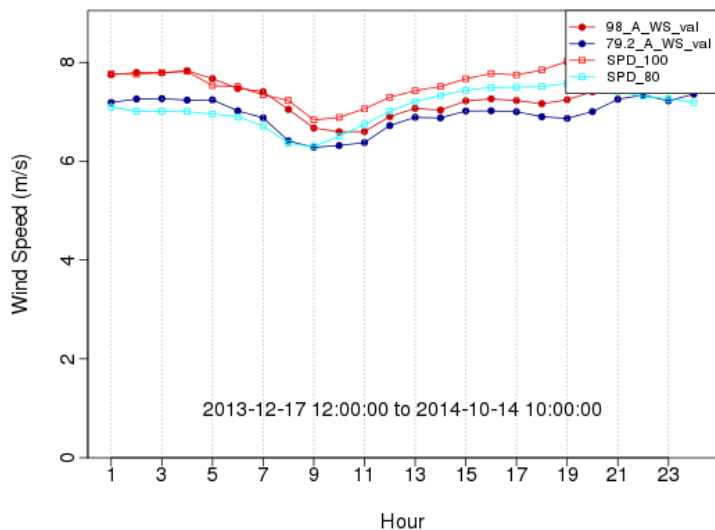
- WRF is built with state-of-the-art data assimilation, dynamic and physics schemes
- WRF is open-source
 - large community of developers
 - updated twice a year
- WRF is fast



Validation of the Atmospheric Model

SUMMARY OF VALIDATION AT 23 PRE-CONSTRUCTION MET MASTS

Met variable	Mean bias	Hourly R ²	Daily R ²
Wind speed	0.09 m/s	0.65	0.82



Methodology for Time Series Energy Modeling

Step 1

Atmospheric Modeling
(e.g. WRF)

- Wind components (u,v,w),
- Temperature,
- Pressure,
- Air Density,
- Relative Humidity,
- etc.

Step 2

Energy Modeling
(e.g. OpenWind)

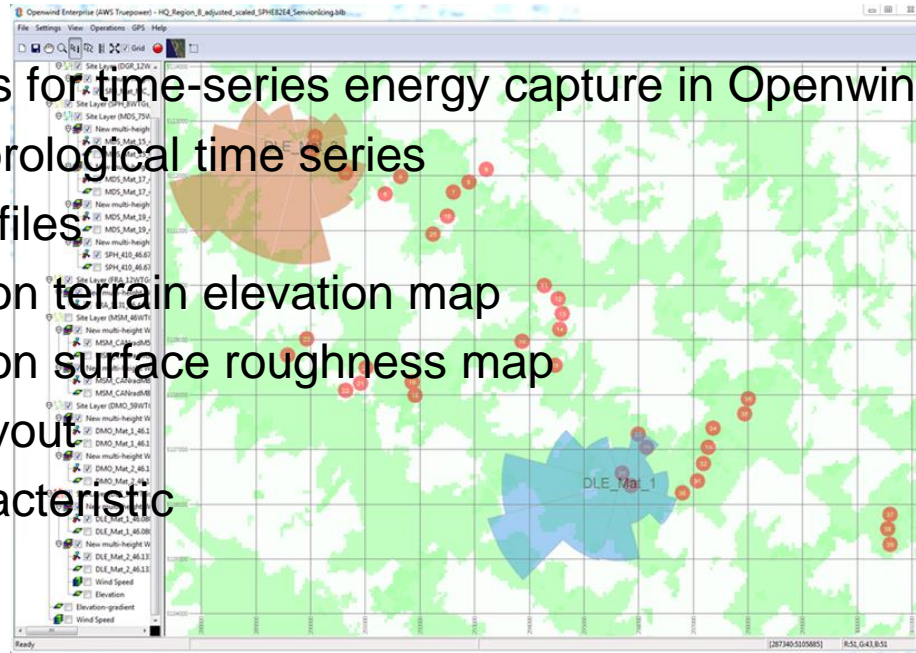
- Gross Energy
- Plant losses
- Net Energy

Time Series Energy Modeling in Openwind

CONVERSION TO POWER

Necessary inputs for time-series energy capture in Openwind:

- ✓ Hourly meteorological time series
- ✓ Binary WRG files
- ✓ High-resolution terrain elevation map
- ✓ High-resolution surface roughness map
- ✓ Wind farm layout
- ✓ Turbine characteristic



* WRG = Wind Resource Grid

Synthetic Wind Power Time Series

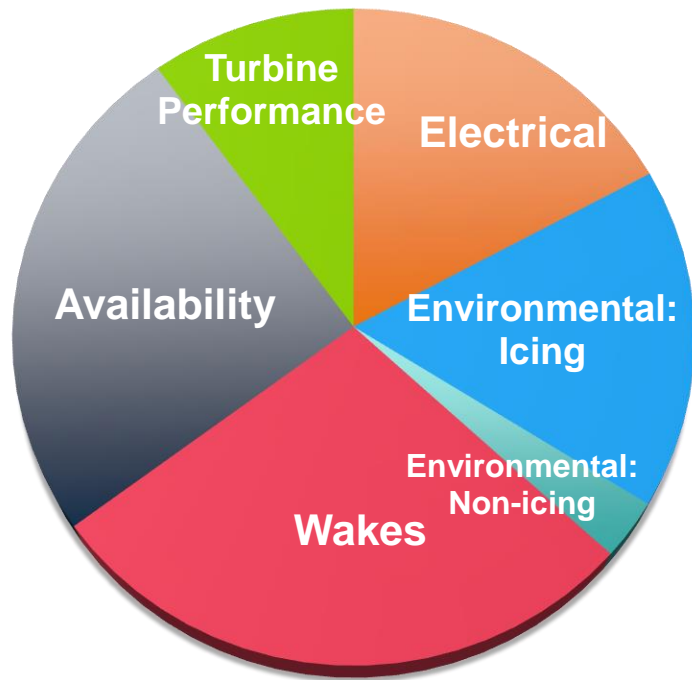
ESTIMATING NET POWER GENERATION

Gross wind power generation

- Plant losses by type:

- ➔ ▪Availability:
 - ❖ Scheduled maintenance & Outages
- ➔ ▪Environmental :
 - ❖ Icing,
 - ❖ Temperature shutdowns,
 - ❖ High wind hysteresis
- Wakes
- Turbine performance
- Electrical

= Net wind power generation



Availability

WIND TURBINE DOWNTIME

- Time-varying wind plant availability is simulated through a Markov Chain
- 18 operational projects providing a total of 52 wind-farm years

Transition matrix								
Availability	(0.99,1]	(0.95,0.99]	(0.85,0.95]	(0.75,0.85]	...	(0.05,0.15]	(0.01,0.05]	(0,0.01]
(0.99,1]	92%	7%	0%	0%	...	0%	0%	0%
(0.95,0.99]	7%	89%	4%	0%	...	0%	0%	0%
(0.85,0.95]	1%	13%	84%	2%	...	0%	0%	0%
(0.75,0.85]	1%	2%	13%	77%	...	0%	0%	0%
...
(0.05,0.15]	4%	2%	2%	1%	...	68%	7%	2%
(0.01,0.05]	1%	1%	2%	2%	...	3%	75%	6%
(0,0.01]	2%	0%	7%	7%	...	8%	6%	35%

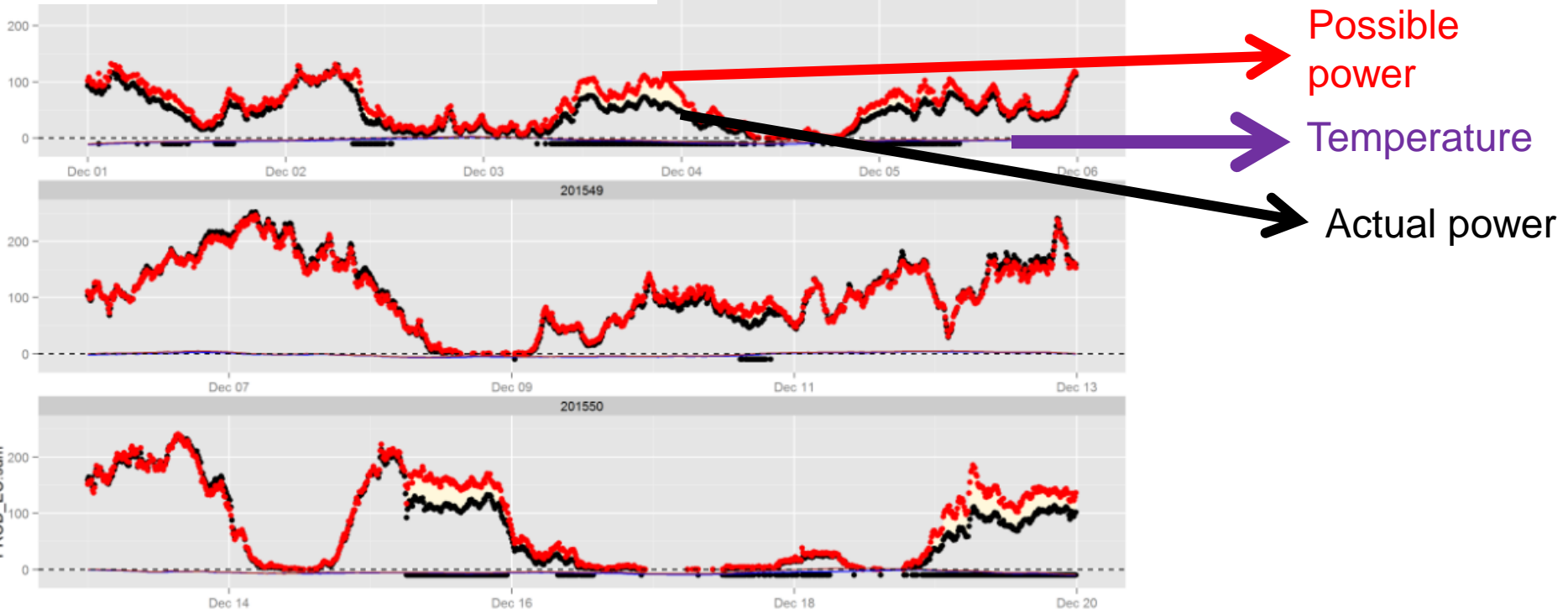
Observed Icing Losses

Wind Plant	Annual Icing Losses
1	3.9%
2	0.5%
3	6.8%
4	1.7%
5	2.2%
6	3.6%
7	20.1%
8	2.7%
9	15.1%
10	2.9%
11	2.2%
12	1.0%
13	4.7%
14	5.8%
15	11.1%
16	0.4%
17	1.1%
18	2.0%

Icing Losses

IDENTIFYING ICING EVENTS FROM SCADA DATA

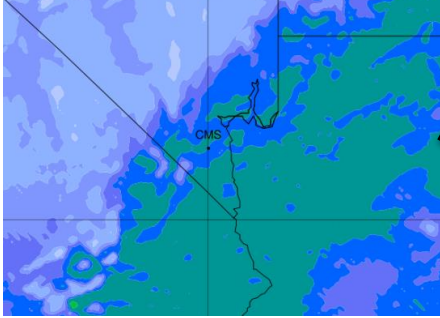
First 3 weeks of December 2015



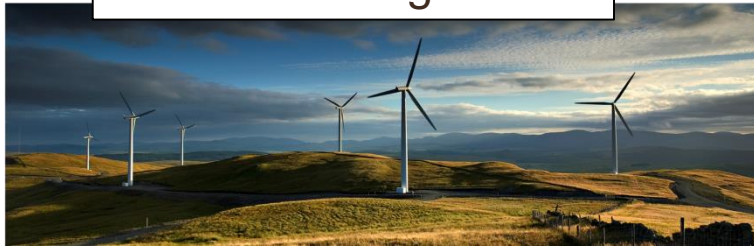
Icing Losses

GENERALIZED ADDITIVE MODEL

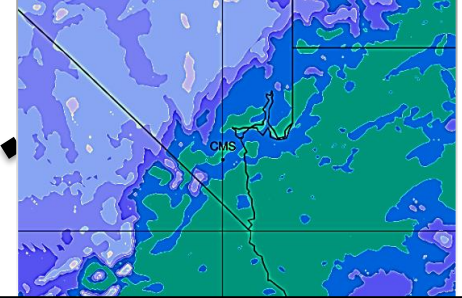
Historical met conditions



Historical icing losses



Simulated met conditions



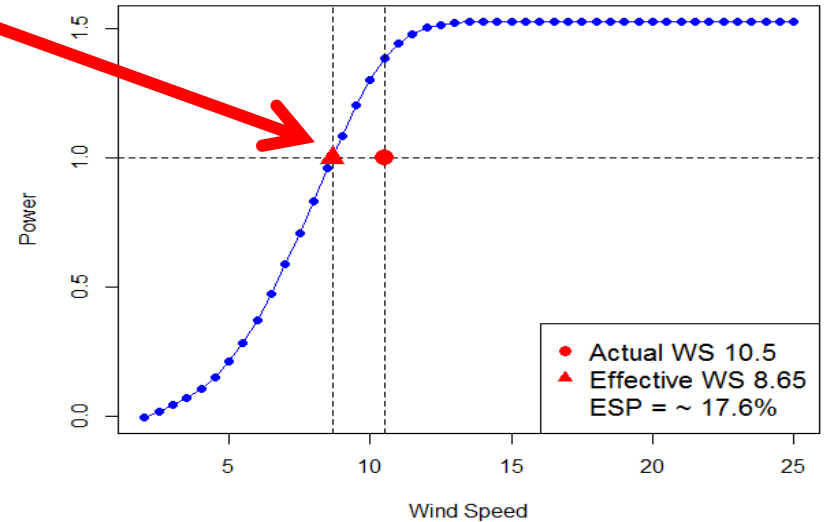
Simulated icing losses



Icing Losses

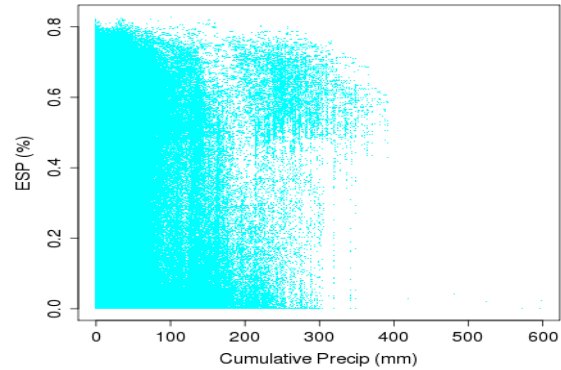
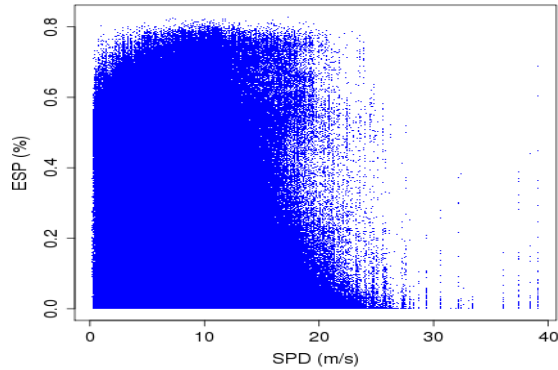
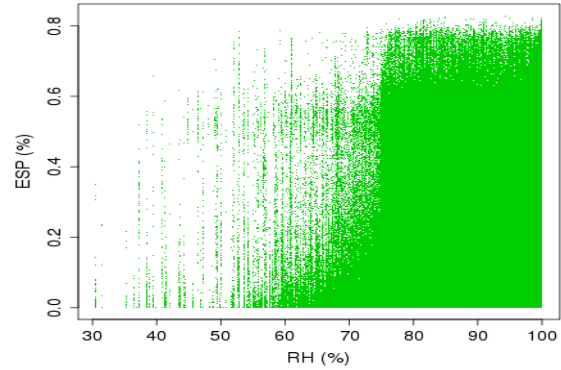
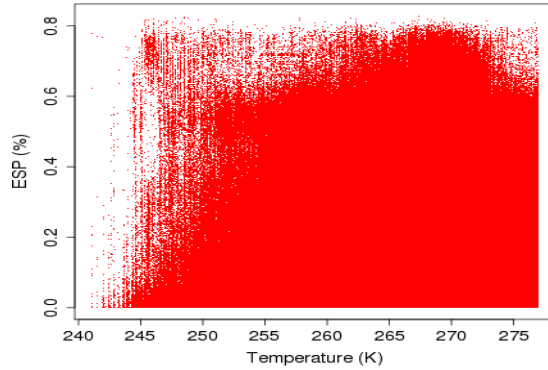
EFFECTIVE SPEED PENALTY

- Predictand (Y) is Effective Speed Penalty (ESP)
- Predictors (X_i) are taken from WRF time series
- Build an icing model at the turbine level
- Train statistical model with a subset of the WRF data under potential icing conditions



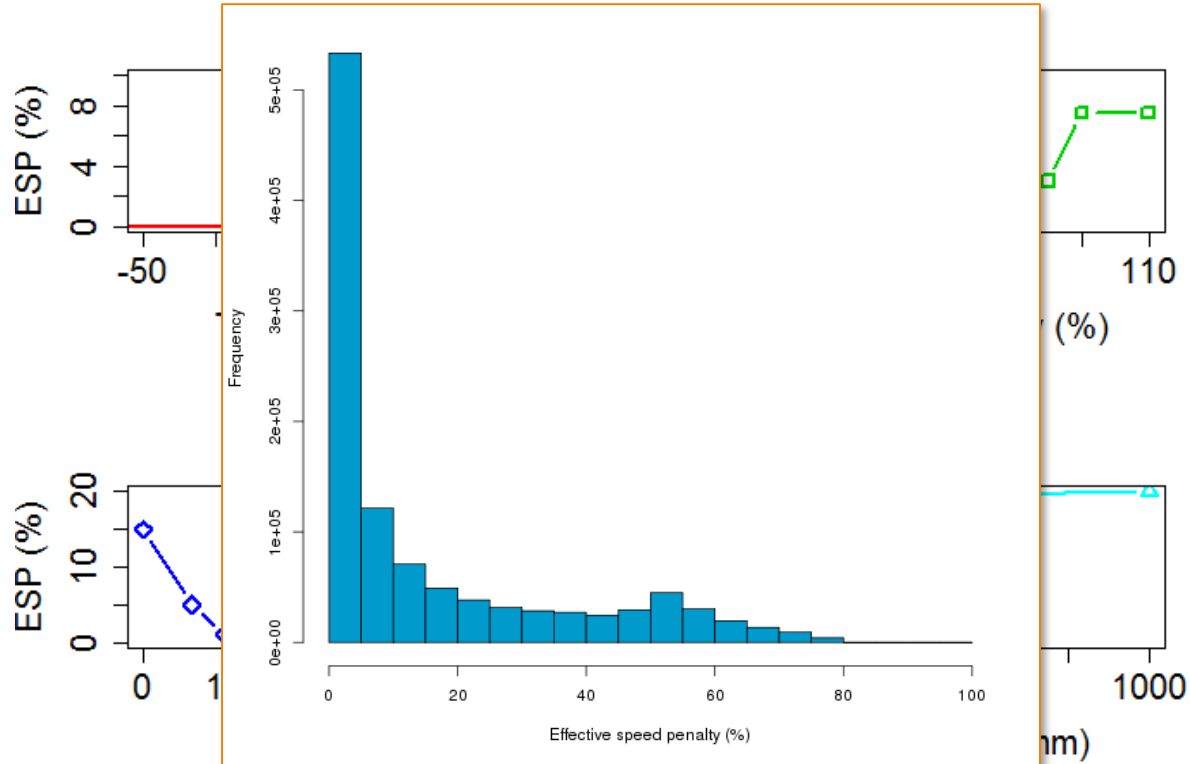
Icing Losses

ESP VS. PREDICTORS



Icing Losses

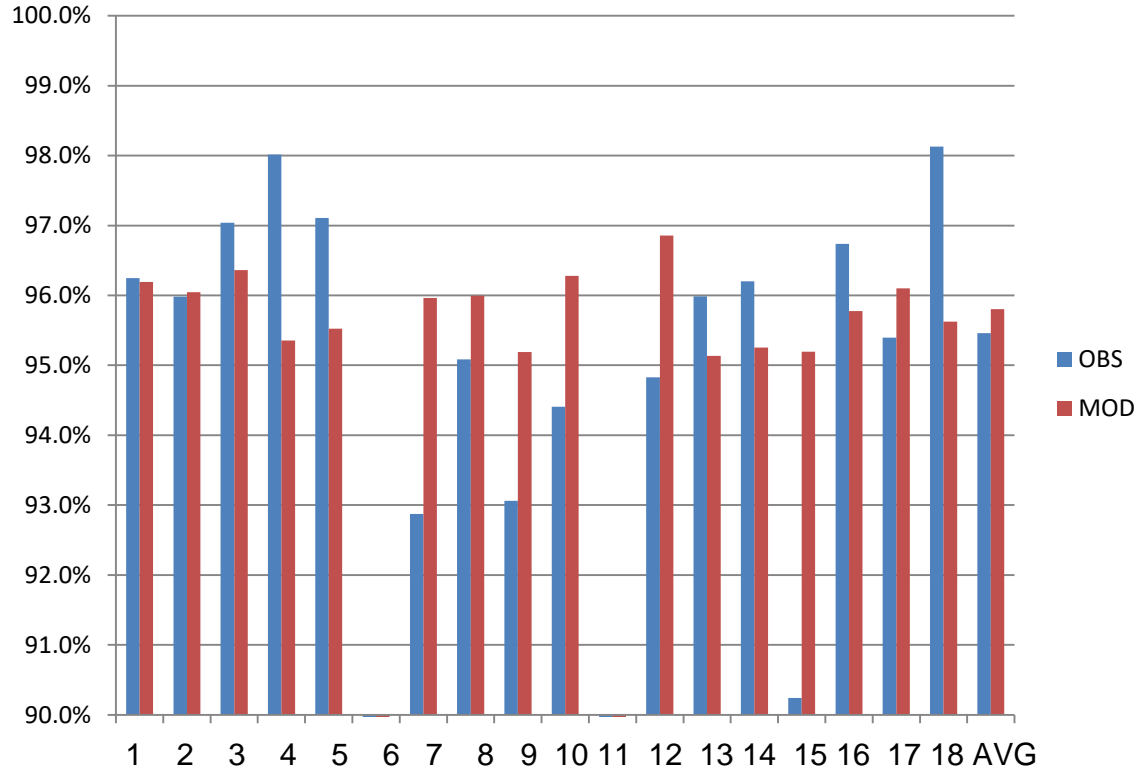
NON-LINEAR FUNCTIONS BASED ON GAM: ESP VS. PREDICTORS



Validation of Wind Power Time Series

AVAILABILITY LOSSES

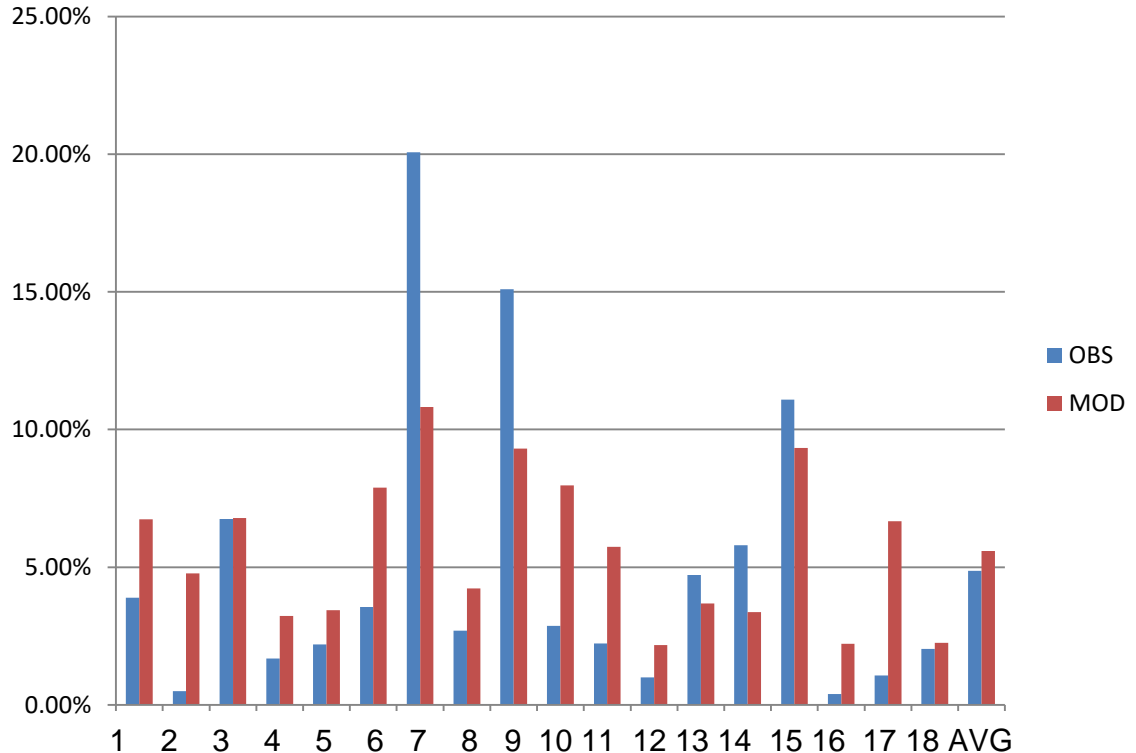
Observed	Modeled
95.5%	95.8%



Validation of Wind Power Time Series

ANNUALIZED ICING LOSSES

Observed	Modeled
4.9%	5.6%



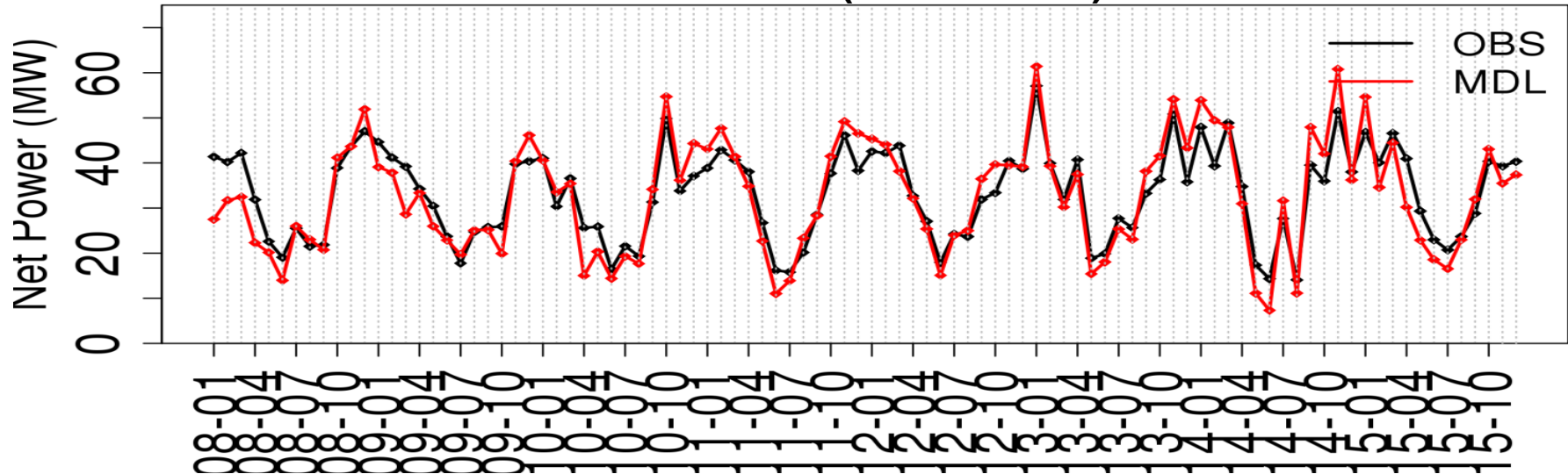
* Annualized over PoR in SCADA data

Validation of Wind Power Time Series

NET WIND POWER GENERATION

Hourly R ²	Daily R ²	Monthly R ²
0.79	0.90	0.92

Wind Farm #2 (GE turbines)

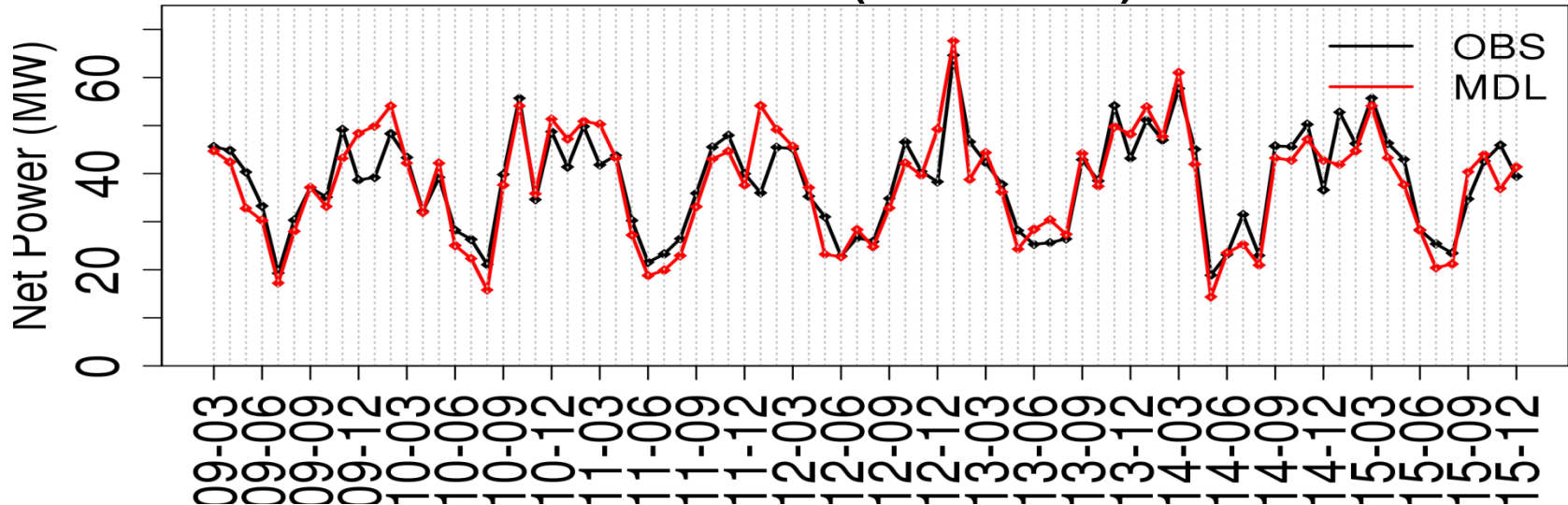


Validation of Wind Power Time Series

NET WIND POWER GENERATION

Hourly R ²	Daily R ²	Monthly R ²
0.81	0.88	0.93

Wind Farm #3 (GE turbines)

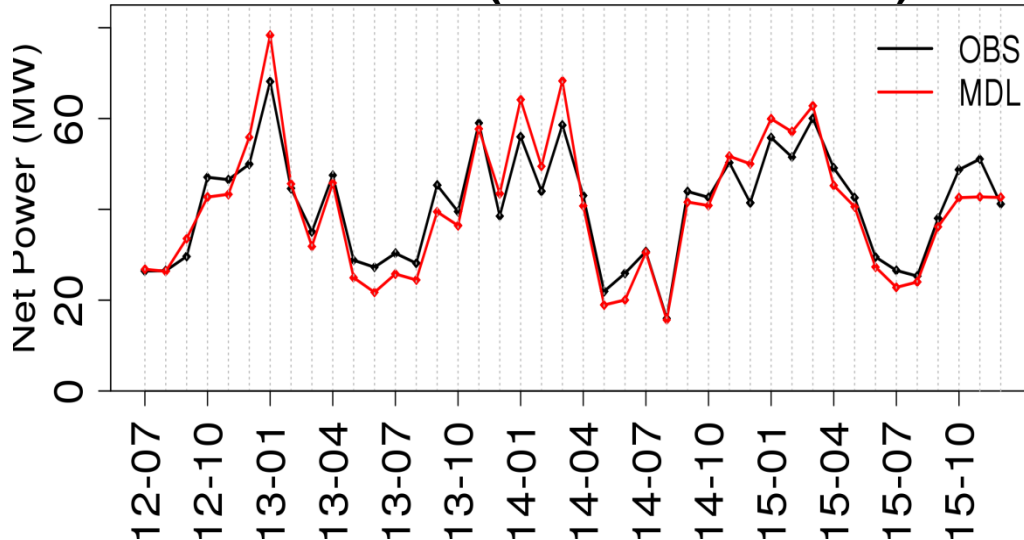


Validation of Wind Power Time Series

NET WIND POWER GENERATION

Hourly R ²	Daily R ²	Monthly R ²
0.86	0.92	0.95

Wind Farm #8 (Enercon turbines)

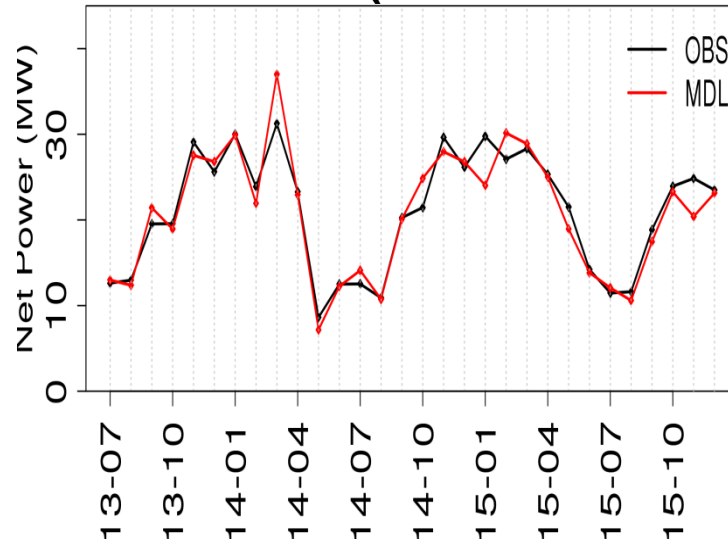


Validation of Wind Power Time Series

NET WIND POWER GENERATION

Hourly R ²	Daily R ²	Monthly R ²
0.83	0.92	0.97

Wind Farm # 12 (Enercon turbines)



Conclusion

KEY ACCOMPLISHMENTS

- Simulated time-varying wind plant losses including icing and the power consumption of the rotor blade heating system
- Simulated net wind power generation are well aligned with the actual generation
- Monthly/seasonal trend in net power are well captured by the simulation system
- On average, modeled icing losses are on par with the observed icing losses although large discrepancies may exist at single wind farm (mainly with spoiler issue)

Conclusion

NEXT STEPS

- Add OEM specific controls to the rotor blade heating system (RBHS) in OpenWind
(e.g. triggers/threshold for start and end of RBHS)
- Add turbine shutdown due to icing loads on blades

Thank you



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