Improved weather forecasts for wind energy applications:
Lessons learned and perspectives based on EWeLiNE

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Current Situation in Germany

- **Installed capacity** (2014): 39.3 GW
  - onshore: 38.2 GW
  - offshore: 1.0 GW

- **Contribution to German power consumption** (2014):
  - wind energy: 9.7% (offshore 2.6%)
  - renewables total: 27.8%

- **Strong increase in offshore wind energy** (Jan-June 2015):
  - 442 new power plants
  - +1.8 GW

Source Illustration: Windenergie Report Deutschland 2014, Fraunhofer IWES
Improved forecasts are required

- Reliable and accurate forecasts of the weather dependent power production are essential for operating transmission systems in a secure way.
- Quality of wind power forecasts depend crucially on the quality of the underlying weather forecast.

**Example 12th April 2015:**
Day-ahead amplitude error: $\Delta_{\text{max}} \approx -4.7$ GW
Probably due to pressure gradient error after cold front.
Research project EWeLiNE

- Overarching goal: improved wind and PV power forecasts (day-ahead)
- Users’ requirements are directly integrated into the R&D activities
How do we proceed to obtain optimized weather forecasts?

1. **Evaluation/Verification**: understand the reasons for the largest day-ahead wind power forecast errors

2. **Optimization approaches**: define methods and test their impact via case studies etc.

3. **Evaluation/Verification**: experiments for longer time periods and evaluate the general performance (including other variables)

4. **Inclusion of optimizations in online-mode**: provide users with improved weather forecasts/products
Improved NWP-forecasts & products: challenges

- The pronounced diurnal cycle of the boundary layer during summer impacts the wind profile
- 3-D wind profiles & non-linear relation between wind and wind power

Availability and quality of wind measurements at hub-height – crucial for verification, data assimilation, and calibration

General: how do we define a good forecast?

Source: http://www.elite.tugraz.at/Jungbauer
Main critical weather situations to consider

- Seasonal dependency:
  - Winter: stable conditions (bias)
  - Sommer: diurnal cycle
- Cold frontal passages
  - temporal and spatial position and intensity of low pressure systems

COSMO-DE-EPS: Wind bias 90-110 m

100 largest day-ahead wind power errors (2012-2014): Synoptic evaluation

A. Steiner
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Numerical Weather Prediction at DWD

**COSMO-EU**
- Spatial resolution 7 km
- 4 Forecasts/day
- (up to 78 h)

**ICON**
- Spatial resolution 13 km
- 4 Forecasts/day
- (up to 180 h)

**COSMO-DE**
- Spatial resolution 2.8 km
- 8 Forecasts/day
- (up to 45 h)

**COSMO-DE-EPS**
- 20 Ensemble forecasts

References:
Can data from power plants be used to improve weather forecasts?

**OSSE-Study based on artificial data:**
- Observation System Simulation Experiment (COSMO-DE + nudging)
- Goal: investigate impact of wind information at hub height

**Setup:**
- 68 reference wind farm sites
- 15 min resolution
- Artificial data: wind speed @ 100m
- Observation error: 2ms-1 (unbiased)
- Perturbations for control:
  - physics (vertical mixing)
  - dynamical core (num. accuracy)
Can data from power plants be used to improve weather forecasts?

**OSSE-Study based on artificial data:**
- Observation System Simulation Experiment (COSMO-DE + nudging).
- Goal: investigate impact of wind information at hub height
- Result: Positive impact of 100m-wind on forecast quality for the first hours (<7h)

**Experiments with real wind and wind power data under way**
- Challenges:
  - data availability (e.g., willingness to provide data for research, costs,..)
  - data quality (e.g., time stamps, internal inconsistencies,..)

Example: OSSE-Study assimilation of artificial wind data at 100m
Improved model parameterizations

- Major challenge: capture and relief stable conditions
- Sensitivity studies - Achievements:
  - Adjusted turbulence parameters lead to lower turbulent diffusion coefficient for momentum (stronger atm. stability)
  - Improvements by artificially increased vertical mixing after sunrise
Improved ensemble generation

- Ensemble forecasts dynamically capture the forecast uncertainty

Varied initial and boundary conditions

Example: Wind speed ensemble forecast with modified initial conditions

BLACK: „operational Setup“ (Nudging + BCEPS)
RED: Combination with LETKF-Data assimilation (KENDA)
Time interval: 18.05-15.06.14

90-160 m Wind: RMSE + Spread

R. Keane
Post-processing for wind forecasts at hub height

- Enhancing direct model output in terms of temporal resolution, additional elements, correction of systematic biases, combination of models...

- Ensemble calibration: Ensemble forecasts suffer from bias and underdispersiveness
  - Ensemble calibration focus on correcting ensemble mean bias and ensemble spread bias
Post-processing for wind forecasts at hub height

Example: COSMO-DE-EPS based ensemble forecast 100m wind speed at FINO 1 (offshore)

Raw Ensemble

Post-processed
- Non-homogeneous Gaussian Regression (NGR/EMOS*)
- Corrected mean-bias and spread-bias

T. Heppelmann

RED: wind speed measurements**
BLUE: ensemble based COSMO-DE-EPS day-ahead forecast

*Schuhen et al. 2012, Mon. Wea. Rev
**Operated by DEWI GmbH.
Summary: lessons learned

- Day-ahead wind power forecast errors correlate with weather situations and vary with season: e.g., frontal passages, lows, diurnal cycle (summer), bias (winter)

- Assimilation of artificial data from power plants indicates positive impacts on the forecast – assimilation with real data under way

- Modified turbulence schemes and optimized ensemble generation show promising results

- Probabilistic forecasts are generally increasing in importance
  - Point-wise calibration increases forecast quality (mean-bias and spread-bias). Challenges: spatial distribution and online available data, developing scenarios, and deal with spatial/temporal correlations
  - Implementation into decision making processes - not straightforward

- Perspectives: the situation is not getting less challenging!
  - Local forecasts from 0h up to several days ahead for secure grid maintenance and planning: nowcasting as well as forecasts for several days ahead are required
  - Enhanced non-weather influence (own consumption, feedback control,..)