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RESEARCH AT ALPHA VENTUS
Eine Forschungsinitiative des Bundesumweltministeriums

Using weather prediction ensembles for optimizing offshore wind forecasts

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[1] Fraunhofer IWES
[2] ForWind

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Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit

Supervisor

Projektträger Jülich Forschungszentrum Jülich

Coordination

Fraunhofer IWES

Outline

- Data
- Baseline: Assume normal errors
- Alternative 1: Variance Inflation
- Alternative 2: Gaussian Ensemble Dressing
- Conclusions

Rave


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Forecast Target:
FINO-1 Met Mast
(wind speed)


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FINO 1

FINO 1
(50m)

FINO 1

Downscaled to 10m

FINO 1

Downscaled to 10m

- Logarithmic assumption

FINO 1

Downscaled to 10m

- Logarithmic assumption
- Matches NWP

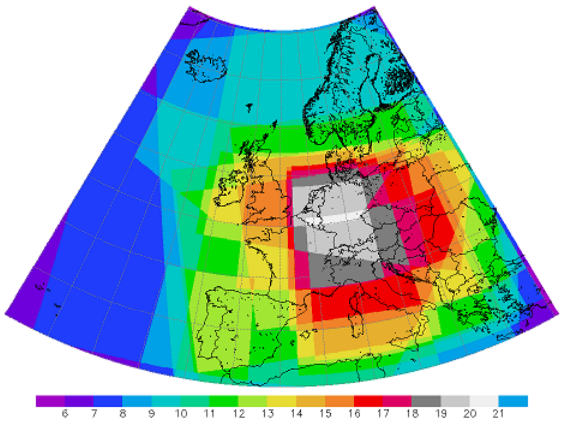
Forecast Input:
Poor Man's Ensemble Prediction System

- Poor Man's Prediction Ensembles
  - 23 deterministic NWP forecasts,
    20 European weather services
  - Based on four different regional models
    (COSMO, HIRLAM, UKMO, ALADIN)
  - Provided by DWD (German Weather Service)

Provided by

- Forecast horizons: 1-48 hrs

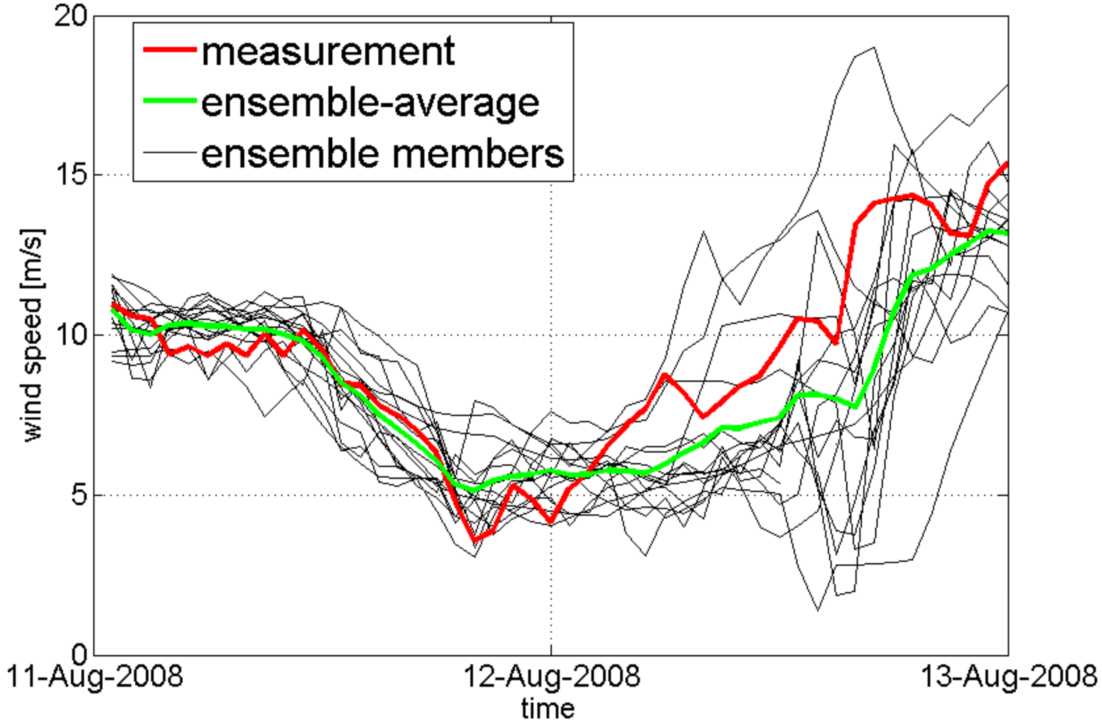
Required Spatio-Temporal Overlap ➔ Ensemble Subset



2007/2008: 12 members with sufficient data

Probabilistic forecasting based on ensemble predictions

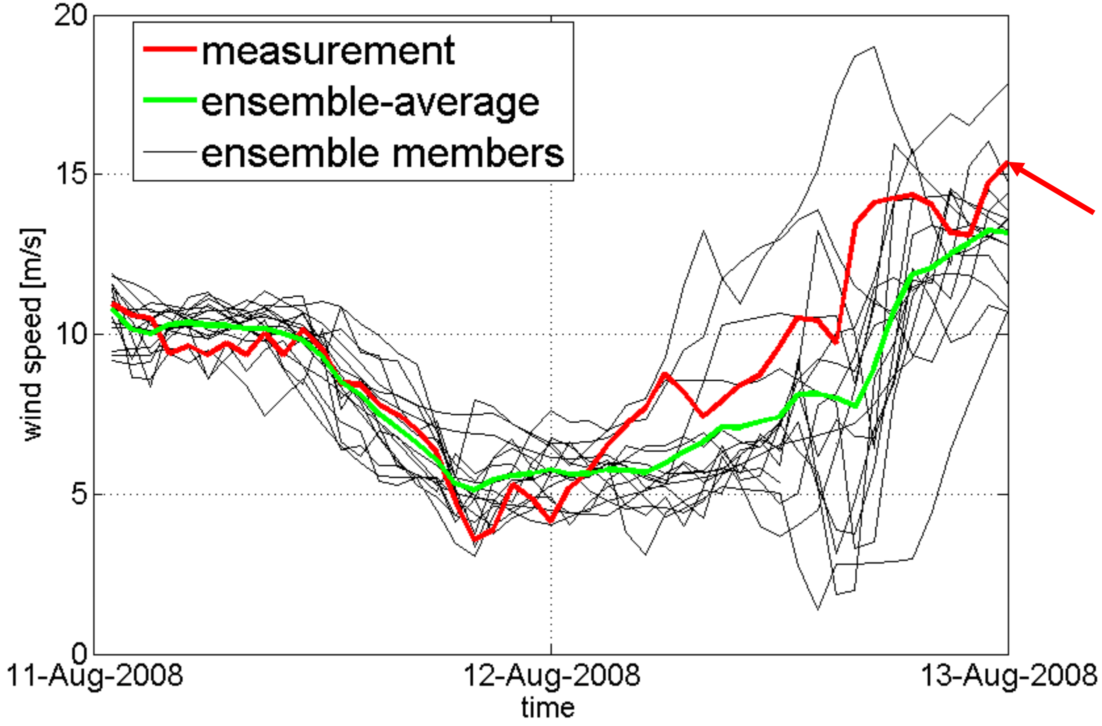
Example of an ensemble prediction



- **Ensembles**:
  Set of same-horizon forecasts

Probabilistic forecasting based on ensemble predictions

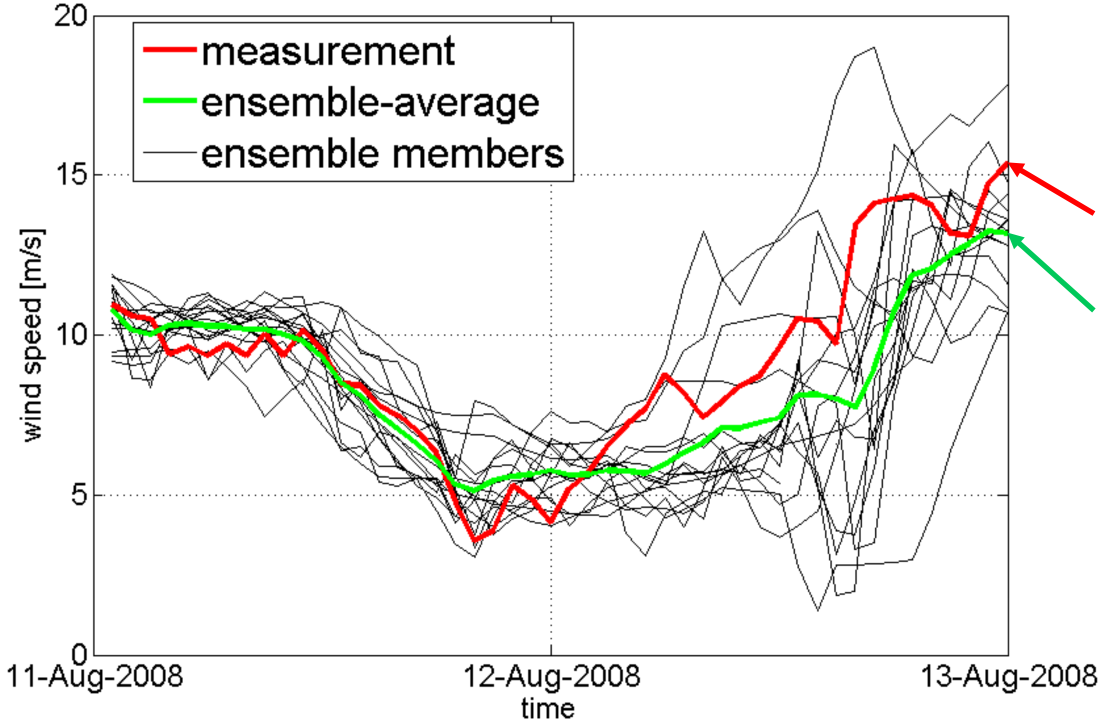
Example of an ensemble prediction



- Ensembles:
  Set of same-horizon forecasts
- Measurement

Probabilistic forecasting based on ensemble predictions

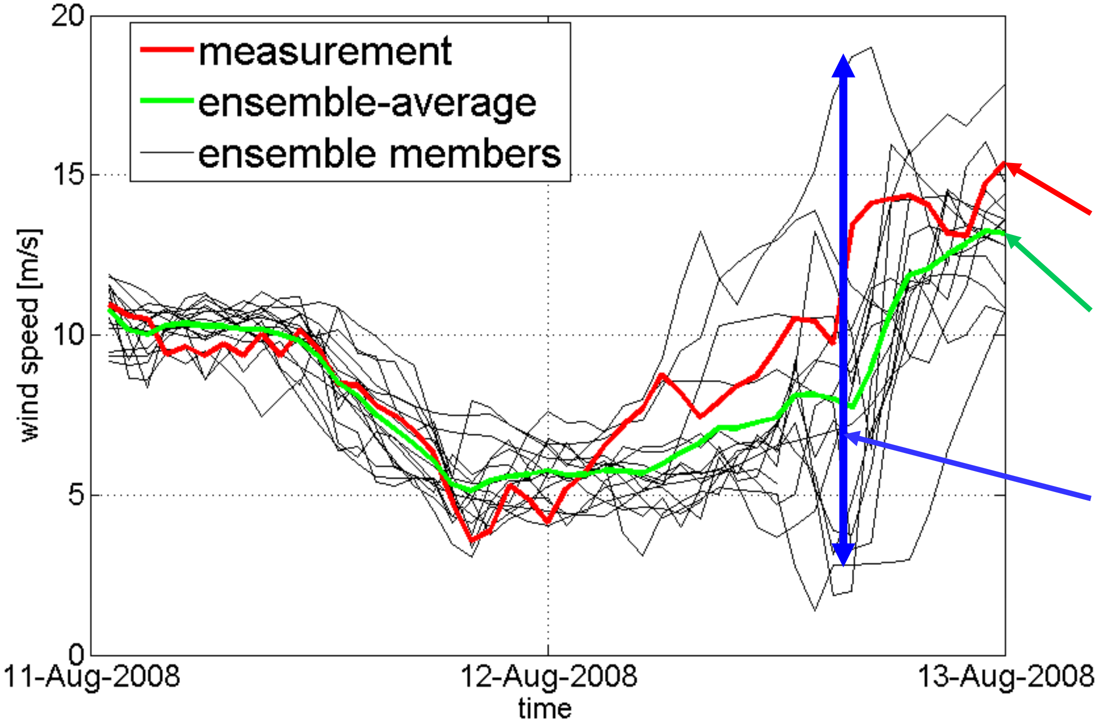
Example of an ensemble prediction



- **Ensembles**:
  Set of same-horizon forecasts
- **Measurement**
- **Ensemble average**:
  (normally) a good forecast

Probabilistic forecasting based on ensemble predictions

Example of an ensemble prediction



- **Ensembles**:
  Set of same-horizon forecasts
- **Measurement**
- **Ensemble average**:
  (normally) a good forecast
- **Ensemble spread**
  (normally) a good indicator of forecast uncertainty

Baseline System: Assume Normal Distributed Error

Assumption: Wind speed forecast error is normal distributed

$$\Delta_{ws} \sim N(\mu, \sigma^2)$$

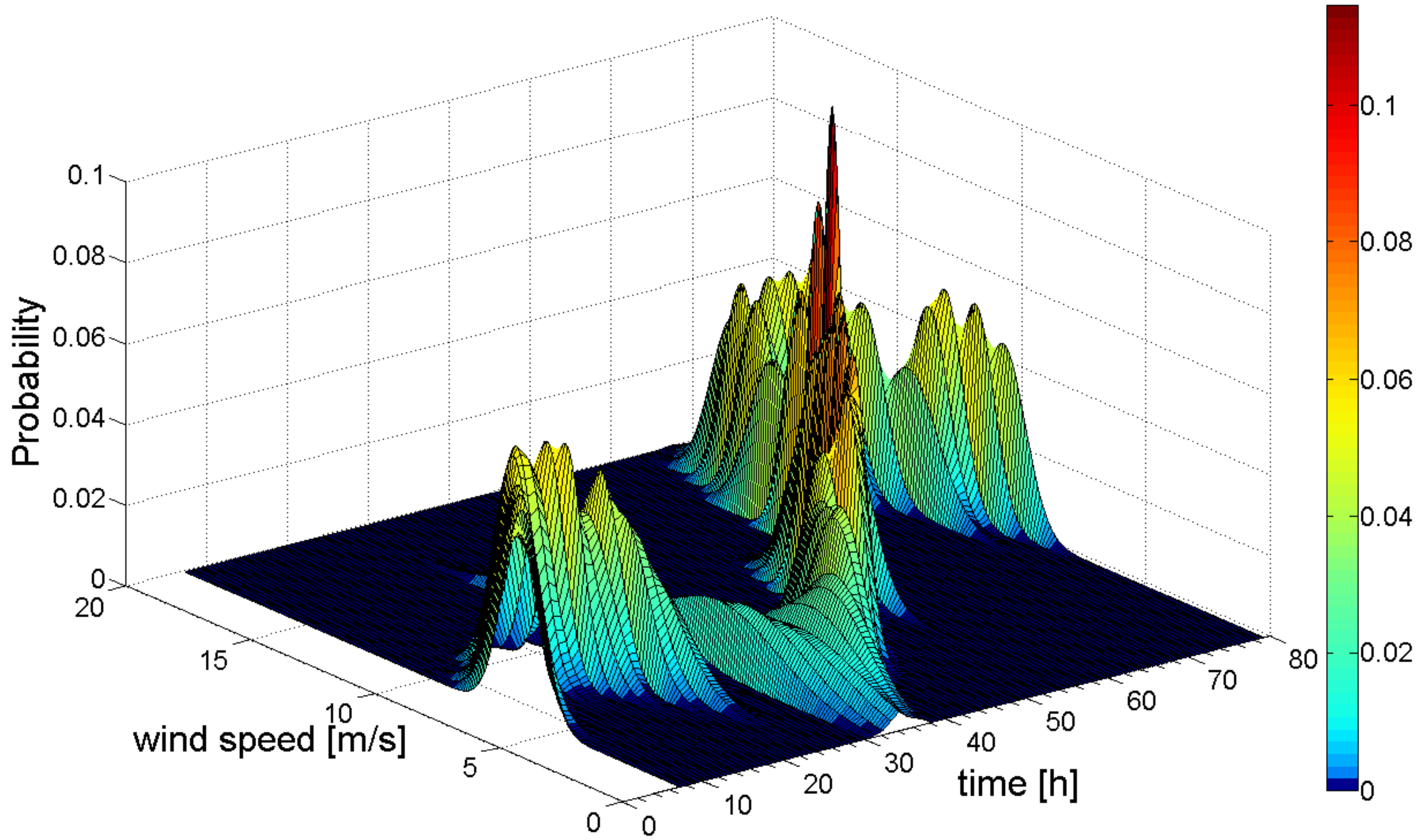
→ Probabilistic forecast at time t is based on a normal distribution

$$forecast(t) \sim N(\mu(t), \sigma^2(t))$$

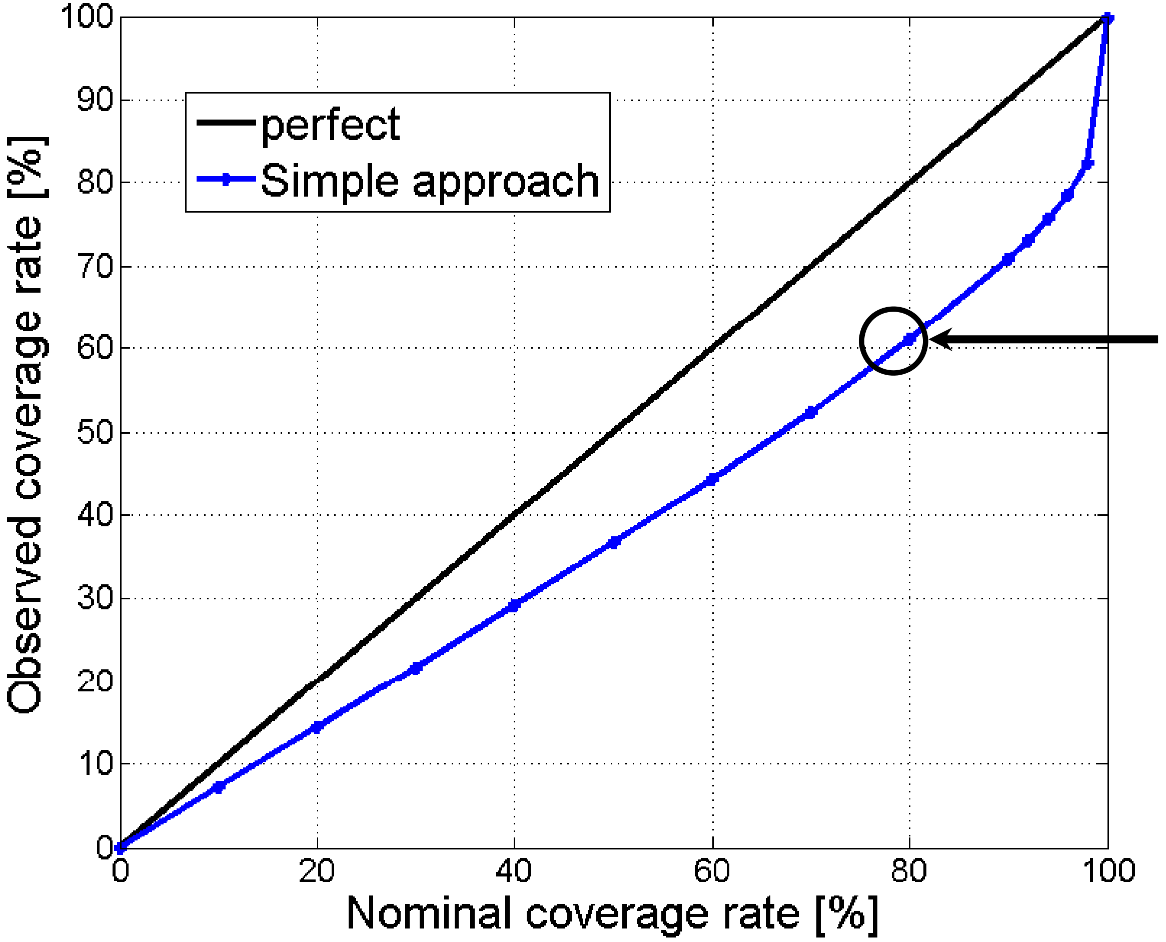
$\mu(t)$ = ensemble average at time t

$\sigma(t)$ = ensemble standard deviation @ t

Baseline Forecast: Normal Assumption



Baseline forecast: Reliability: do the distributions match?



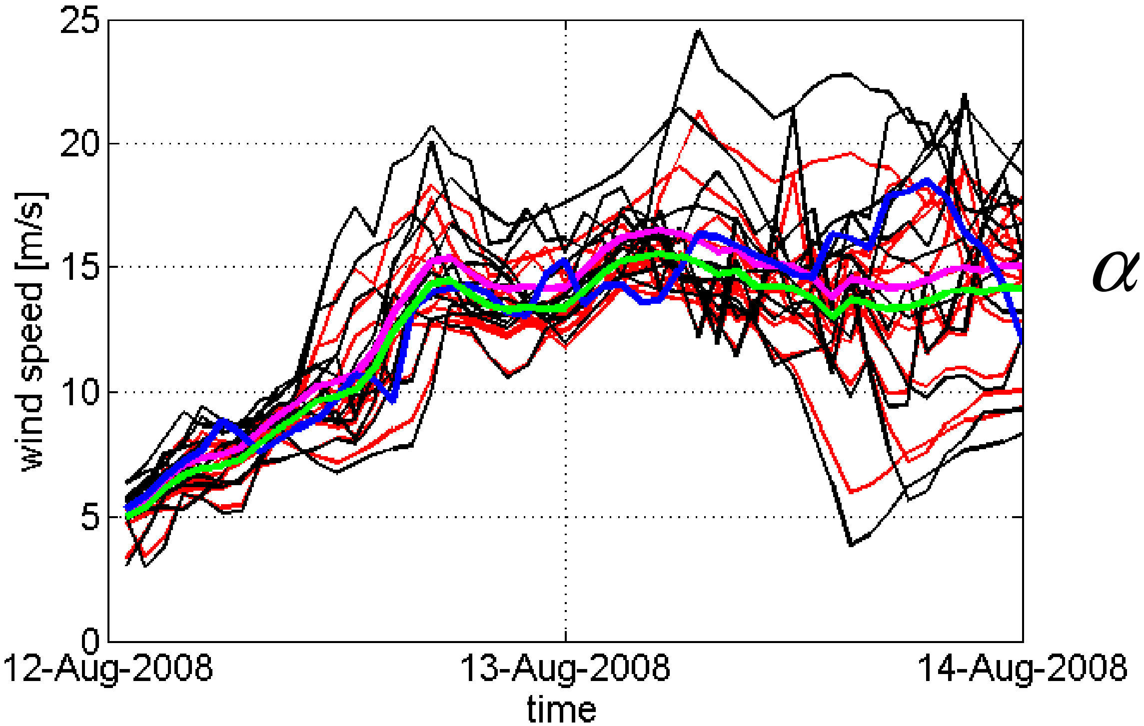
e.g. 60% of all measure-ments within the 80%-Interval
(avg. across horizons)

→ Not so good

(Averaged over forecast horizons)

Alternative 1: Variance Inflation

$$S_{cal,i}(t) = \alpha * \mu(t) + \beta * (S_i(t) - \mu(t))$$



α, β derived from historical 2007 data

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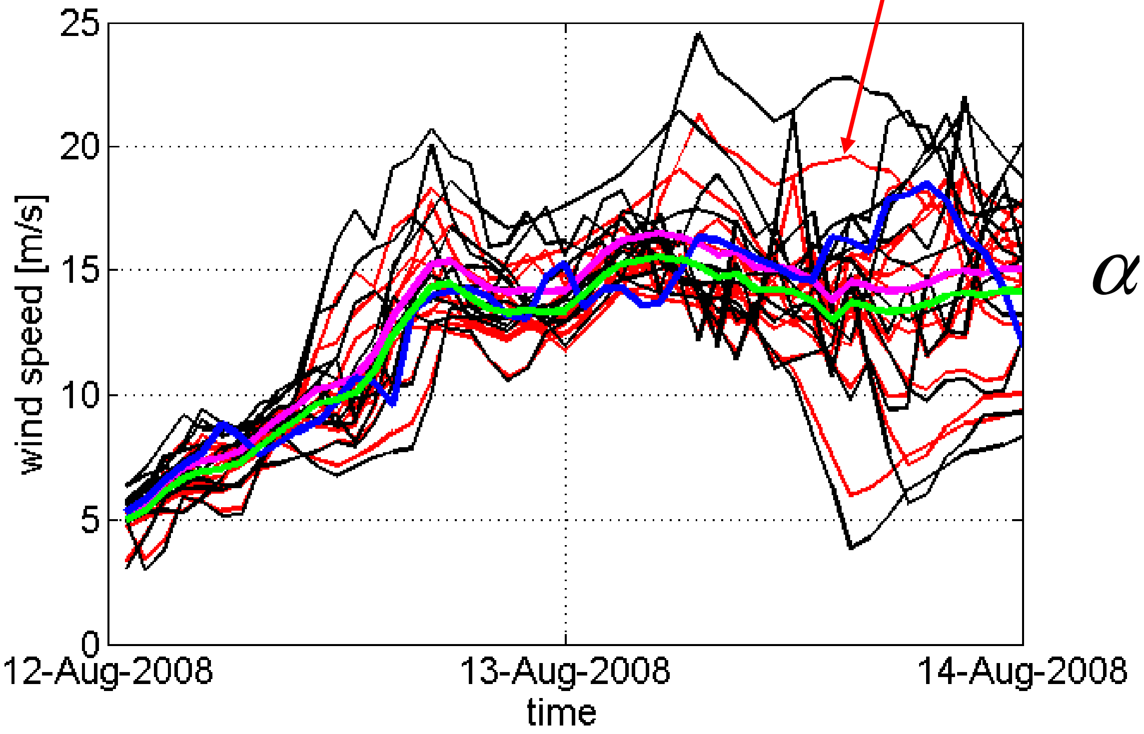

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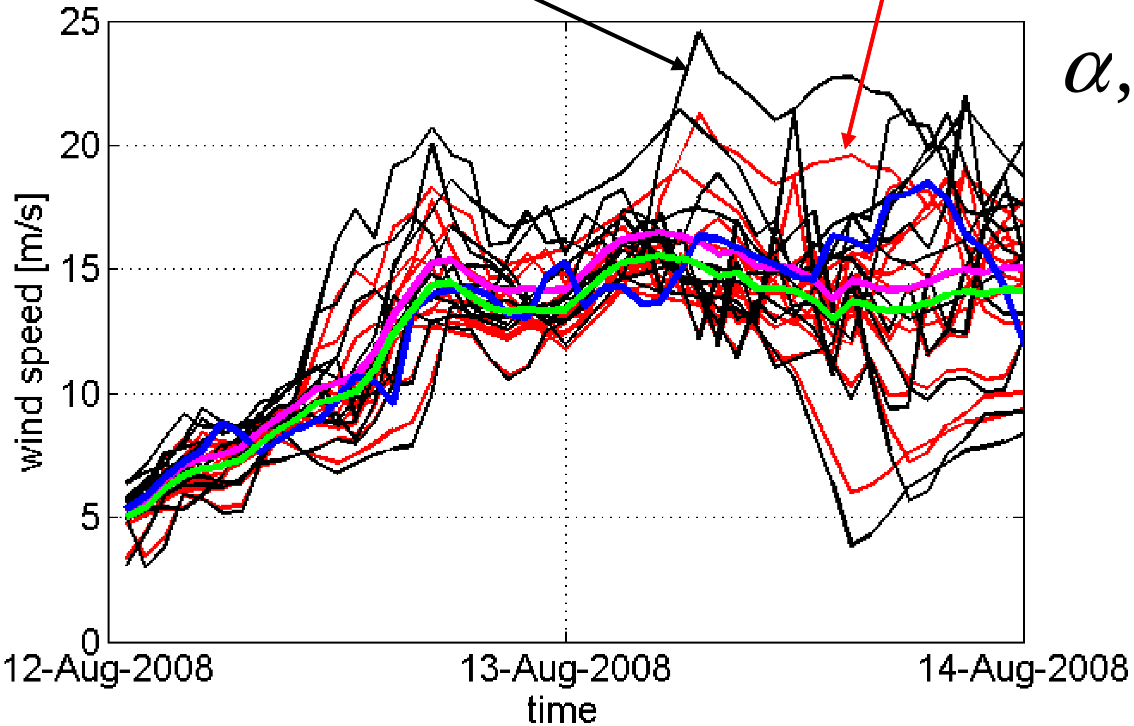
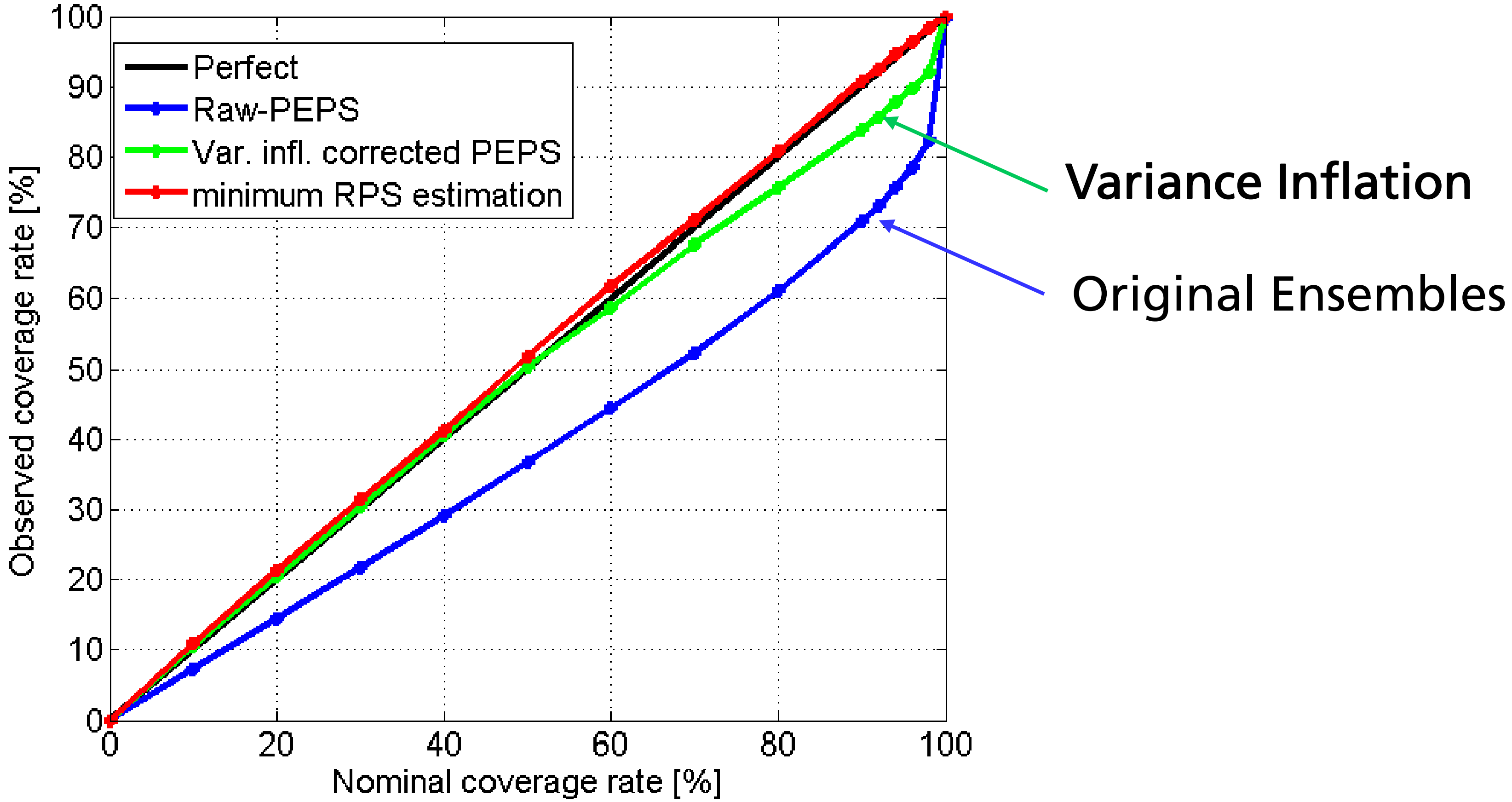


α, β from regression against 2007 measurements

Variance Inflation: Improved Reliability

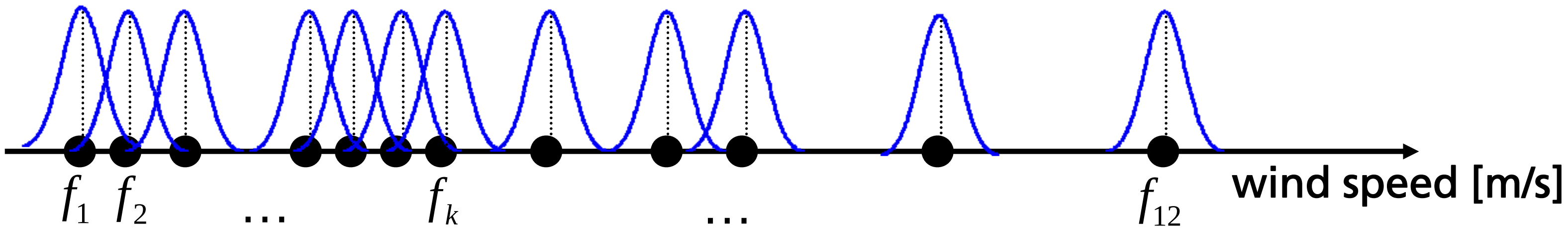


Alternative 2: Gaussian Ensemble Dressing

1.) Normal distribution around each ensemble member at time t:

$N_t(f_k, \sigma^2)$ with: f_k forecast of ensemble member k

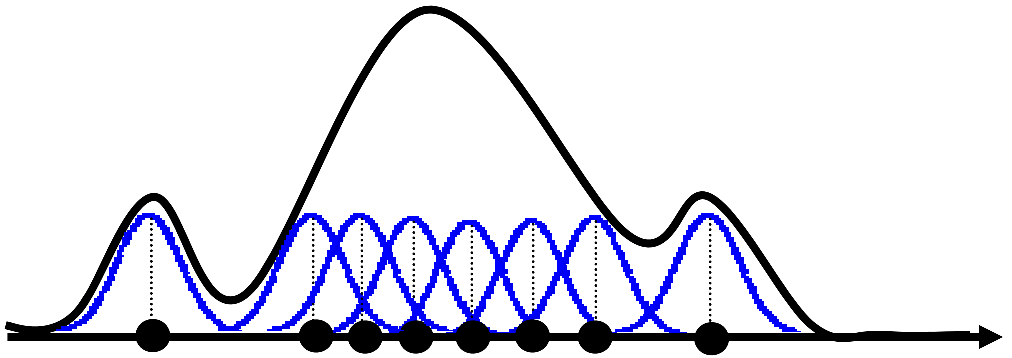
σ standard deviation, same for all k



Gaussian Ensemble Dressing

2.) Weighted linear combination

$$P_t = \sum_{k}^{12} w_k N_t(f_k, \sigma^2) \quad \text{with} \quad \sum_{k}^{12} w_k = 1$$



Gaussian Ensemble Dressing

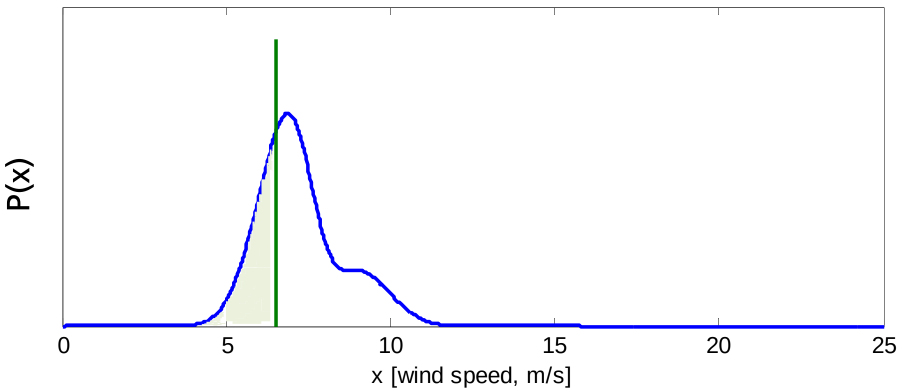
3.) Optimization of the unknown parameters: $w_1, w_2, \ldots, w_{12}$ & σ

$$P_t = \sum_{k}^{12} w_k N_t(f_k, \sigma^2)$$

… by minimization of *"Ranked Probability Score (RPS)"*

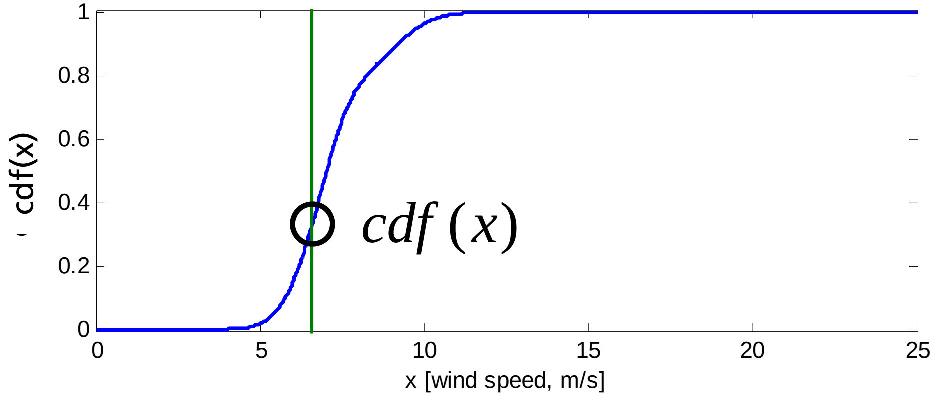
Minimize the cdf difference at each time, t
(over 2007 measurements)

Gaussian Ensemble Dressing: RPS



Probability Density Function

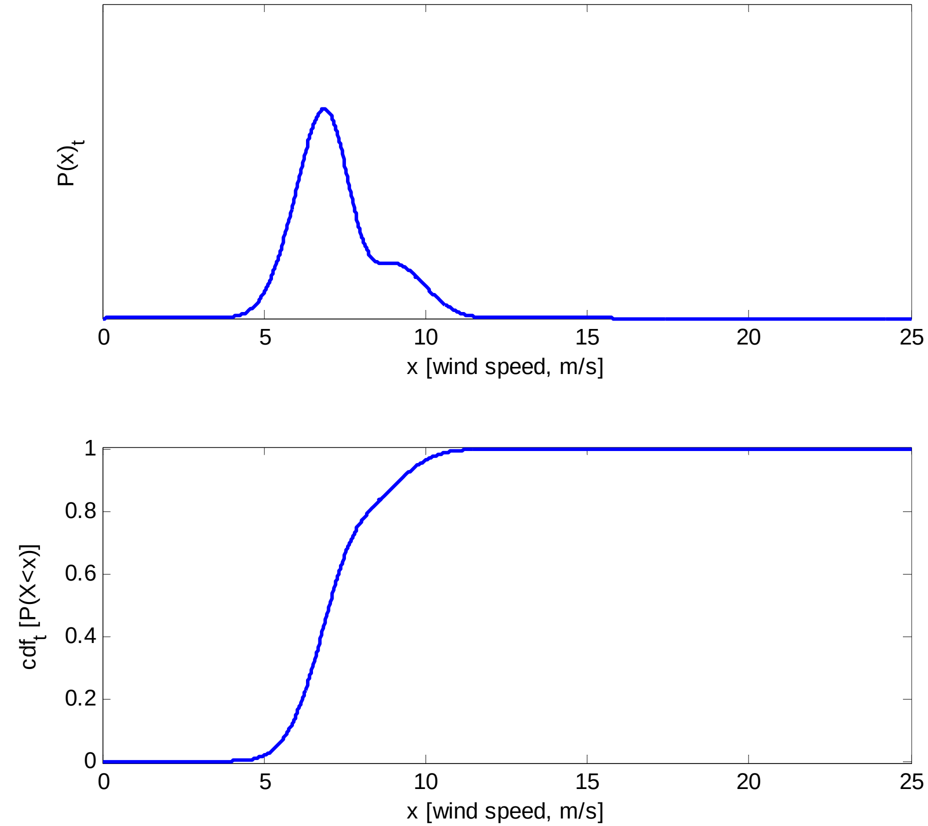
$$P(x) = prob(meas = x)$$



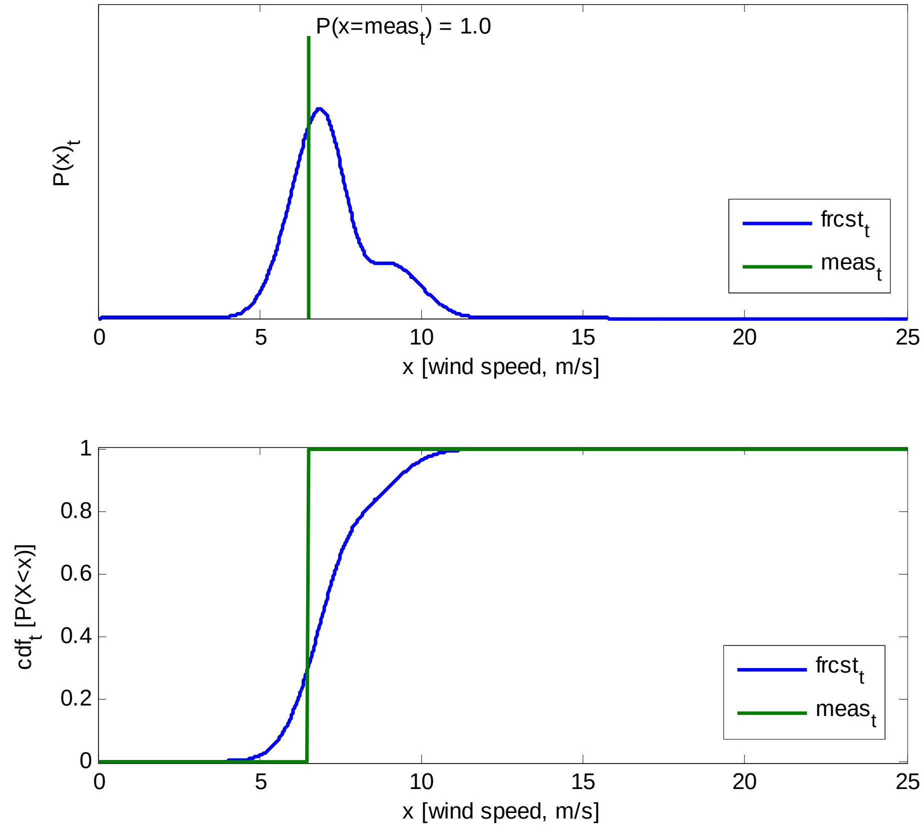
Cumulative Density Function

$$cdf(x) = prob(meas \le x)$$

Gaussian Ensemble Dressing: RPS

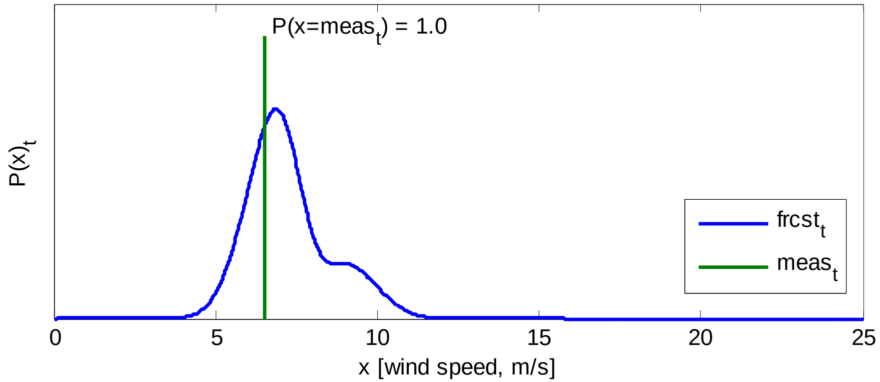


Gaussian Ensemble Dressing: RPS

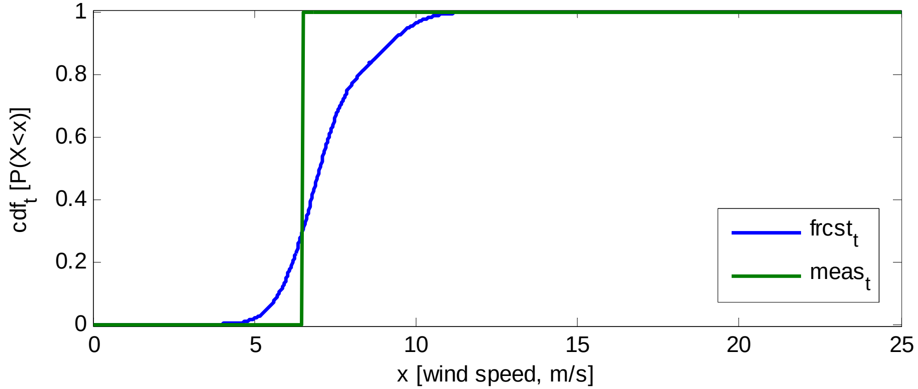


Measurement probability: 1.0

Gaussian Ensemble Dressing: RPS

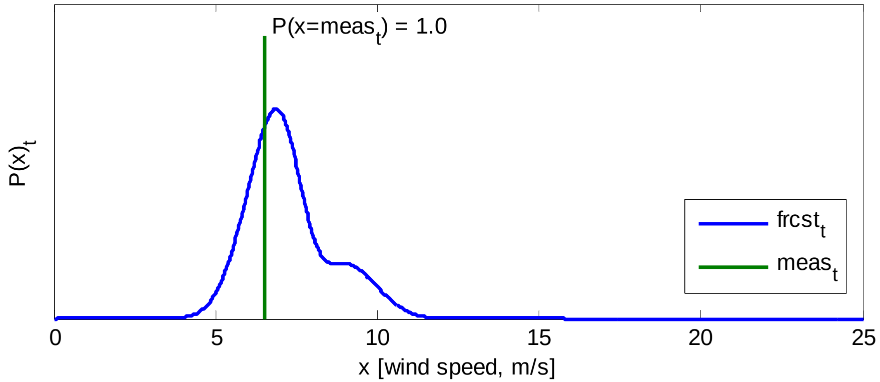


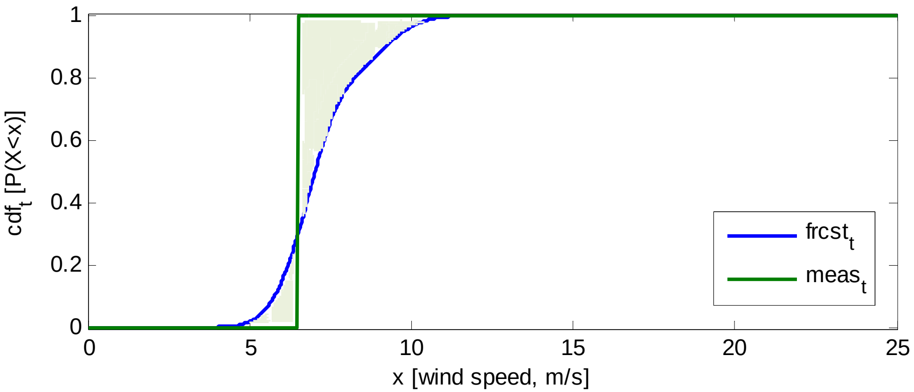
Measurement probability: 1.0



Measurement cdf: step function

Gaussian Ensemble Dressing: RPS





➔ **RPS:** a function of cdf error²

$$\Delta cdf\,(t,h) =$$

$$\int_{s\in windspeed} \left(cdf_h^{\,frcst}(s,t) - cdf^{\,meas}(s,t)\right)^2 ds$$

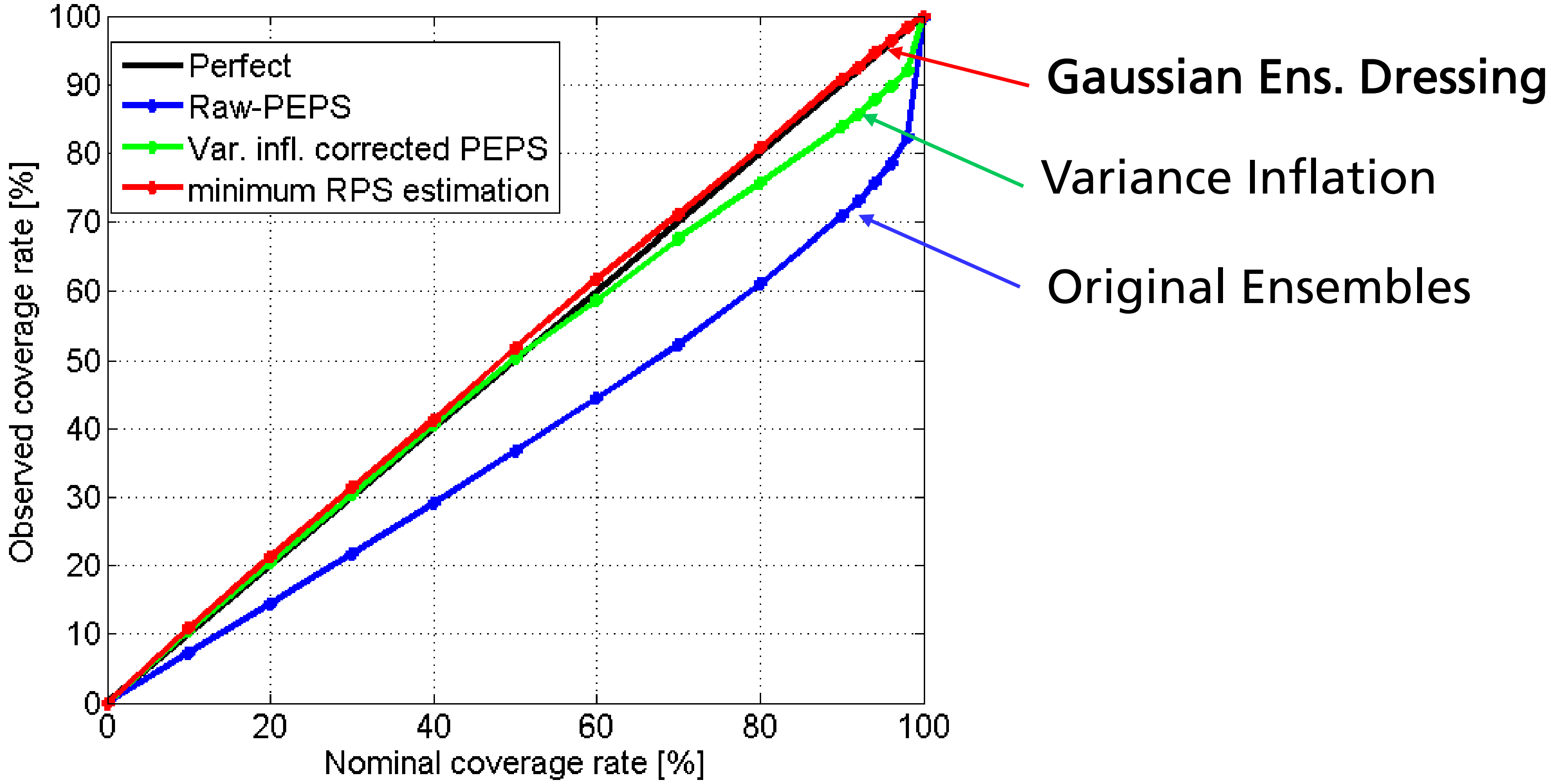
Gaussian Ensemble Dressing: Optimization

- Optimization cost function: RPS over time, horizons

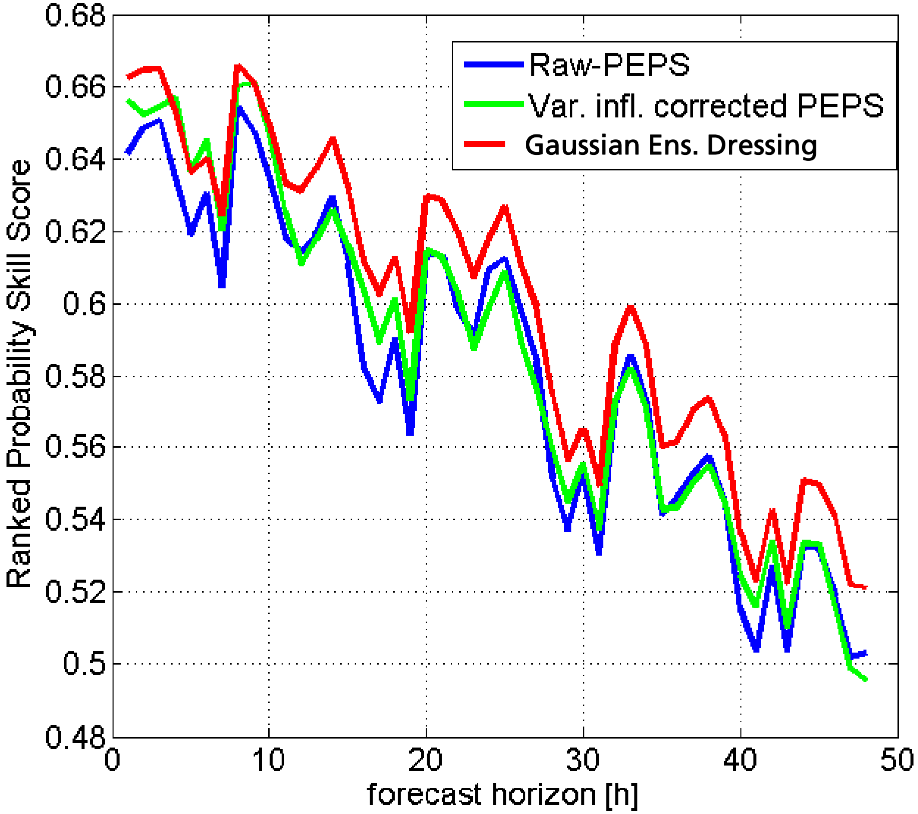
$$RPS_{\cos t} = \iint_{time,\ horizons} \Delta cdf\,(t,h)\ dt\,dh$$

- Optimization algorithm: Simplex

Gaussian Ensemble Dressing: Best Reliability



Gaussian Ensemble Dressing: Best skill across forecast horizons



Ranked Probability Skill Score:

$$RPSS = 1 - \frac{RPS}{RPS_{climatology}}$$

0 → no skill
1 → perfect skill

Gaussian Ensemble Dressing has clearly higher skill

Conclusions

- Variance scaling is an improvement, but…
- Gaussian Ensemble Dressing is best
  - highest reliability
  - highest skill
- Optimization via RPS minimization works
- Next…
  - Probabilistic power forecasts for Alpha Ventus