Prediction Models for Wind Speed at Turbines in a Farm with Application to Control

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The Aeolus project

This work is part of the EU-FP7 project with the title: Distributed Control of Large - Scale Offshore Wind Farms (Aeolus).

The problem from a control point of view

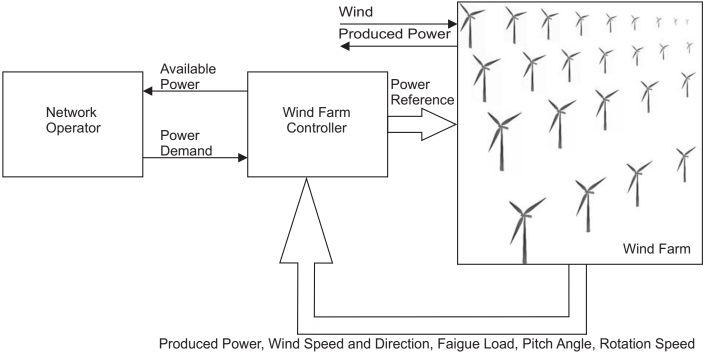


Figure: Block diagram illustrating the centralised control problem.

Wind speed models for farm level control

Motivation and objectives

Motivation

- Modern control design methods is model based.
- Prediction models are used explicitly (MPC) or implicitly (LQG).
- A wind farm model includes the dynamics of the wind field.
- The important time scale is the average time for wind to travel between turbines which is typically 1 minute.

The objective is then:

Develop a method for making models for wind speeds at turbine positions in a wind farm where the available measurements are standard signals from the turbines. The models must be suitable for prediction.

Results from the literature and new challenges

Results from the literature

- In Sørensen (2005) it is concluded that the the prediction of wind speeds from upwind turbines is not useful.
- Nielsen (2004) reports useful models for *point* wind speed at separation 300 m but a very weak relation over 600 m.
- Point wind speed coherence functions in e.g. Panofsky (1984) also support the above statement.

New challenges

- Try to develop methods that improves prediction performance over distances typical for a wind farm.
- A hypothesis is that the effective wind over the rotor should be more predictable.

Estimation of effective wind speed

Estimation task

Estimation of effective wind speed can be approached as a standard estimation problem.

$$\dot{x} = f(x, u, w) \ ,$$
$$y = h(x, u, v)$$

Given the system model above in SS form and the input u output y estimate the state x.

- x is the state which would include the effective wind speed.
- u is the input i.e. blade pitch and generator torque or power reference
- w is process noise which maybe drives the wind model.
- y is measurements e.g. rotor speed, generator speed, produced power and maybe more.
- v is measurement noise.

Approaches from the literature

- Models used are either one or two inertia drive train models.
- The literature investigated uses a Kalman filter (KF) to estimate rotor torque.
- From this rotor torque plus rotor speed and pitch a direct calculation of wind speed is performed based on c_P tables.
- Consequently, no wind speed model is used.

Estimation model

One inertia drive train model plus wind speed model

State equations

$$I\dot{\omega}_r = T_r - T_g \ ,$$

$$\dot{v}_t = -a(t)v_t + n_1 \ ,$$

$$\dot{v}_m = n_2 \ ,$$

$$T_r = \frac{1}{2}\rho v_r^3 A c_p(\lambda,\beta)\frac{1}{\omega_r} \ , \ \lambda = \frac{\omega_r R}{v_r} \ ,$$

$$T_g = \frac{p}{\mu\omega_r} \ ,$$

$$v_r = v_t + v_m$$

Tower was initially included both gave to poor observability.

Measurement equations

$$\omega_m = \omega_r + v_1 \ ,$$
$$v_n = v_r + v_2$$

Detailed wind speed model

- The wind turbulence model is time varying as it depends on average wind speed.
- This improves performance.

$$dv_t = -a(v_m)v_t dt + dw_1 \ ,$$

$$dv_m = dw_2 \ ,$$

$$w \in W(Q) \ ,$$

$$Q = \begin{pmatrix} Q_{11}(v_m) & 0 \\ 0 & Q_{22} \end{pmatrix} \ , \ Q_{11}(v_m) = \frac{\pi v_m^3 t_i^2}{L}$$

$$a(v_m) = \frac{\pi v_m}{2L}$$

Resulting filter

- Based on the above models.
- A extended continuous-discrete Kalman filter has been developed.
- It has acceptable observability.
- An reasonably white prediction errors.

An example of the obtained estimates is seen below

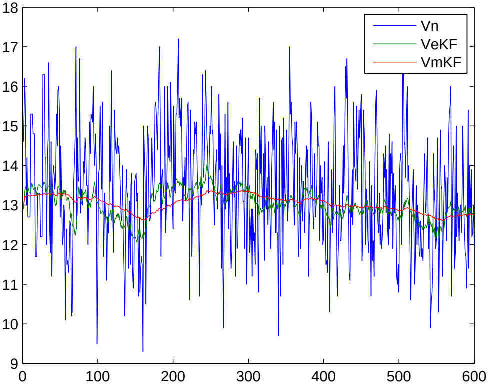


Figure: Comparison of nacelle wind speed and estimated effective wind speed.

Measurements

Vestas kindly provided 1 second measurements from the OWEZ farm for the project.

The OWEZ farm

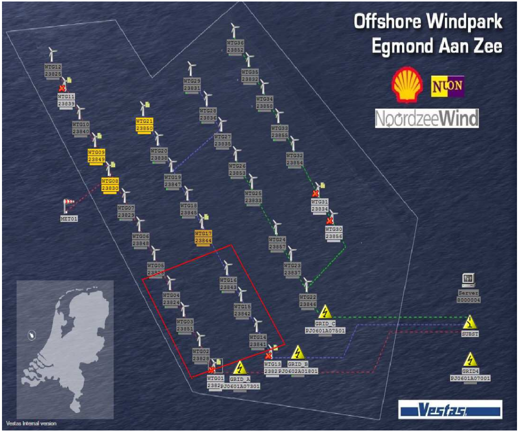


Figure: Layout of OWEZ. The six turbines in the red box is the ones there are measurements for.

Example of 1 days measurements

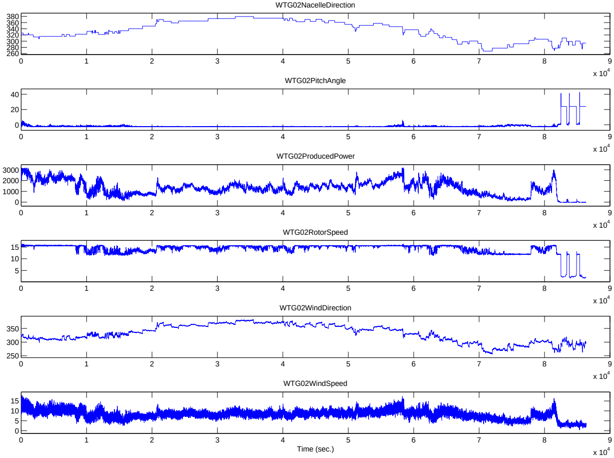


Figure: Time plot for signals from WT02 for one day 2009-02-11.

Simple linear time invariant models

For single input single output (SISO) systems a linear time invariant (LTI) model can be defined as follows.

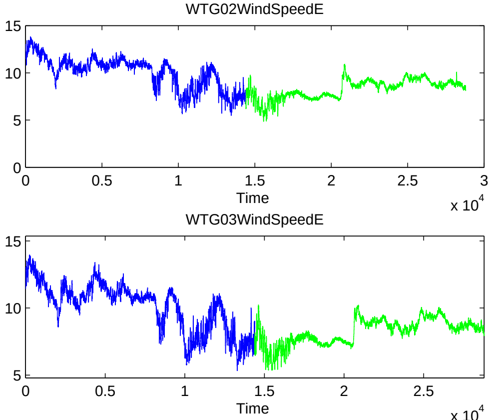
$$y(t) = G(q^{-1})u(t-n_k) + H(q^{-1})e(t)\ ,\ e(t) \in \mathrm{ID}(0,\sigma^2)$$

$$G(q^{-1}) = \frac{B(q^{-1})}{A(q^{-1})}\ ,\ H(q^{-1}) = \frac{C(q^{-1})}{D(q^{-1})}$$

ArxDel	ARX model with delay. $n_a = n_b = 2, n_k = 60, C(q^{-1}) = 1, D(q^{-1}) = A(q^{-1})$.
BJDel	Box-Jenkins model with delay. $n_a = n_b = n_c = n_d = 2, n_k = 60$.
Per	Persistence model, no input from upwind i.e. $\hat{y}(t+k\|t) = y(t)\ \forall\ k$. $A(q^{-1}) = 1 - q^{-1}, B(q^{-1}) = 0$.

Estimation and Validation

- For estimation the first 4 hours is used.
- And for cross validation the next 4 hours is used as illustrated in the figure.



Performance measures

- The RMS error is the standard error estimate for the predictions.

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y(t) - \hat{y}(t|t-k))^2}$$

- The Fit is how much of the standard deviation in the output that is explained by the model.

$$\text{Fit} = 1 - \frac{\text{RMS}}{\hat{\sigma}_y}$$

Results for nacelle wind speed

Fit (%)			
Pred. hor.	ArxDel	BJDel	Per
1 sec.	37.558	42.233	28.535
30 sec.	23.943	32.062	-9.159
60 sec.	23.937	31.548	-6.071
∞	23.937	32.153	
RMS (m/s)			
1 sec.	0.816	0.755	0.934
30 sec.	0.994	0.888	1.187
60 sec.	0.994	0.894	1.227
∞	0.994	0.886	

Table: Predictability for nacelle wind speed using one upwind turbines and LTI models.

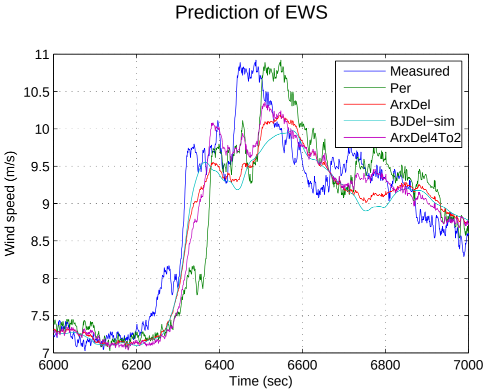
Results for effective wind speed

Fit (%)				
Pred. hor.	ArxDel	BJDel	Per	ArxDel4To2
1 sec.	94.466	94.520	94.380	94.454
30 sec.	68.346	67.928	59.516	64.846
60 sec.	66.862	66.056	52.501	61.178
∞	65.208	65.736		55.140
RMS (m/s)				
1 sec.	0.055	0.054	0.056	0.055
30 sec.	0.314	0.318	0.402	0.349
60 sec.	0.329	0.337	0.472	0.386
∞	0.345	0.340		0.445

Table: Predictability for effective wind speed using one upwind turbines and LTI models.

One minute prediction example

The figure below zooms in on one of the largest gusts in the validation data.
It is clear that a simple prediction model based on the first or second upwind turbine outperforms the persistence method.



Conclusion

Effective wind speed estimation

- In this paper an estimator for effective wind speed is developed.
- This estimator includes the wind speed in a more “correct” way compared to the estimators found in the literature.
- Using the estimator the effective wind speed for six turbines in the OWEZ farm has been estimated.
- The effective wind speed is more suitable for predictions compared to the nacelle wind speed.

Predictability in a real wind farm

- Based on simple classical models the prediction error for this effective wind speed can be reduced with 30% using a upwind turbine compared to the persistence method.
- This reduction is for a prediction horizon of 1 minute and a distance of 632 m.
- The smallest standard deviation for this prediction error is 0.33 m/s corresponding to a 95% confidence interval at ±0.66 m/s which can be sufficiently small to be useful.
- When the distance is approximately doubled to 1277 m the reduction goes from 30% to approximately 15%.