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Abstract

This investigation is part of the EU FP7 project "Distributed Control of Large-Scale Offshore Wind Farms". The overall goal in this project is to develop wind farm controllers giving power set points to individual turbines in the farm in order to minimise mechanical loads and optimise power. One control configuration examined is distributed control where turbines only communicate with their nearest upwind neighbors. Design of such controllers needs wake models and these models should ideally be distributed. This paper compares two simple multiple wake models for this purpose. The study is based on real full scale data. The modelling is based on so called effective wind speed. It is shown that there is a wake for a wind direction range of up to $\pm$ 20 degrees. Further, when accounting for the wind direction it is shown that the two model structures considered can both fit the experimental data. However, both models estimate a weaker wake than suggested by the well known Jensen model.

Keywords: Multiple wake model; experimental data; parameter estimation; distributed models.

1 Introduction

This work is part of the EU FP7 project "Distributed Control of Large-Scale Offshore Wind Farms" with the acronym "Aeolus".

1.1 Motivation

The overall goal in Aeolus is to reduce fatigue and optimize power production in a offshore wind farm. The idea is to do this by designing farm level controllers that distribute power set points to all turbines in the farm based on measurements from all turbines i.e. as a closed loop controller. To do this in a optimal way the control design has to exploit models of the relation between turbines in a farm through the common wind field they share. The final goal is a model that based on available measurements from the turbines including turbine loading and perhaps including a meteorological mast can predict the wind speed at all turbine positions. It is crucial that the model includes the turbine loadings represented by e.g. the thrust coefficient as this is what the farm level controller can change by changing power set points at individual turbines. As distributed control is one of the methods used in the project it is an advantage if the model can be made distributed in the sense that the wind at a turbine can be predicted from information only from its neighboring upwind turbine.

1.2 Previous work

In the literature much research on wake models can be found. There are focus on complex model approaches as CFD in e.g. [1, 2, 3]. There are also simpler models suggested in [4, 5]. Most of the research are on single turbine wakes but work on multi wakes and meandering can also be found [1]. However, verification on commercial scale wind farm is limited.

1.3 Contribution in this paper

The contribution in this paper is:

- A simple distributed model structure
- An experimental design and finally
- Estimated parameters based on eight turbines in a full scale wind farm.

In the following first the wind farm and measurements are described. Then the important notion of effective wind speed is briefly explained. Important experimental conditions are also discussed. Then two model structures are presented and the results from fitting them to data are discussed. Finally a conclusion is made.

2 The offshore farm and measurements

2.1 Choice of a wind farm

The wake effect from one turbine to another is influences by many factors e.g. turbulence intensity and atmospheric stability. The most important is however, the distance between

turbines. The wake effect will naturally decrease with the distance. Inter turbine distances, in commercial farm, are typically from 3.3 D (rotor diameter) e.g. at Lillgrund Wind Farm in Sweden to 7.5 D e.g. at Egmond aan Zee (OWEZ) in the Netherlands. A small inter turbine distances has the advantage of a large wake effect. On the other hand, the results from the study is more relevant if they represent a typical wind farm.

Another key issue in the approach taken here is the access to sufficient turbine parameters for model based estimation of a term called effective wind speed (EWS), which in effect is the output of a filter that estimates the mean wind over the rotor disc. Finally, it is necessary that the measurements system can sample from several turbines with the correct timing. The sampling frequency necessary for the control design in the Aeolus project is 1 Hz.

Fortunately, there was a choice between a number of potential wind farms. The name of the chosen offshore farm remains confidential. It consists of a number of large commercial multi mega Watt turbines. The smallest inter turbine distances is 5.5 D which is a typical distance for offshore farms.

2.2 Measurements

To focus on multiple wakes it is important to measure from as many turbines in a row as possible. The SCADA system on the wind farm used here could not sample more than eight turbines simultaneously. Consequently, eight turbines in a row on the south west border of the farm have been selected for the measurement campaign. The signals in table 1 are measured with 1Hz for each turbine.

Turbine signals	MET Mast signals
Generator RPM	Air temperature
Nacelle direction	Wind direction
Pitch angle	Wind speed
Power	
Power reference	
Roter RPM	
Wind direction	
Wind speed	

Table 1: Measured signals on all turbines and on the meteorological mast.

3 Effective wind speed

Measuring the relevant wind speed at eight turbine positions in a farm is a problem on its own. Using the nacelle anemometer directly is not possible as the reading changed with pitch even though the ambient wind does not change. Using devices like LIDAR or SODAR is too expensive and unpractical especially for several turbines. The best measuring device for the effective wind speed, that a wind turbine experiences, is the wind turbine itself.

Using the turbine as a measuring device facilitated by an extended Kalman filter build around a simple dynamic turbine and wind model. Here follows a short description of the EWS estimator. For full details please see [6].

For the purpose of EWS estimation the turbine is described as a first order dynamical system:

$$I_r\dot{\omega}_r = T_r - T_g, \tag{1a}$$

$$T_r = \frac{1}{2}\rho v_r^3 \pi R_r^2 C_p(\lambda,\beta)\frac{1}{\omega_r}, \tag{1b}$$

$$\lambda = \frac{\omega_r R_r}{v_r}, \tag{1c}$$

$$T_g = \frac{P}{\mu\omega_r} \tag{1d}$$

The inputs to the system are the effective wind speed v_r, the pitch angle β, and the generator torque T_g. The state ω_r is the rotor speed for the lumped single inertia I_r, driven by the rotor and generator torques according to (1a). The rotor torque T_r is given by (1b) where ρ is the air density, R_r is the rotor radius, and λ is the tip speed ratio, defined in (1c). C_p is the aerodynamic efficiency and is a non-linear function of the blade pitch angle and tip speed ratio. The produced power P is related to the generator torque and rotor speed according to (1d) where μ is a constant parameter describing the generator efficiency. The function C_P along with parameters I_r, R_r, and μ are known, see [6].

In order to estimate the effective wind speed v_r, it needs to be described as a state in the system. To this end, the system (1) is augmented with the second order wind speed model described in (2). Note that v_r is split into two components with respect to frequency, where v_t describes the faster variations and v_m models the slower "10 minute average" wind speed. The signals w_1, w_2 are independent Wiener processes with incremental covariance matrix V_w.

$$dv_t = -a(v_m)v_t dt + dw_1, \tag{2a}$$

$$dv_m = dw_2, \tag{2b}$$

$$v_r = v_t + v_m, \tag{2c}$$

The parameters for the wind model are as follows:

$$V_w = \begin{pmatrix} V_{11}(v_m) & 0 \\ 0 & V_{22} \end{pmatrix}, \tag{3a}$$

$$a(v_m) = \frac{\pi v_m}{2L}, \tag{3b}$$

$$V_{11}(v_m) = \frac{\pi v_m^3 t_i^2}{L} \tag{3c}$$

where L is a turbulence length scale parameter and t_i is the turbulence intensity. Note that the dynamics and variance of v_t in (2a) depend on v_m. The parameters are set to:

$$L = 170.1, \quad t_i = 0.1, \quad V_{22} = \frac{2^2}{600}. \tag{4}$$

The choice of V_{22} is based on the approximation that the standard deviation of the change in average wind over 10 min is 2 m/s.

Measurements of the power production P, the pitch angle β, the rotor speed ω_r, and the nacelle wind speed are used. The first two are assumed to be noise free. The uncertainty of the rotor speed measurement is modeled by:

$$\omega_m = \omega_r + v_1, \tag{5}$$

where v_1 is a white Gaussian noise process. The nacelle wind speed measurement may roughly be considered as a distorted measurement of the effective wind speed. Its uncertainty is modeled by:

$$v_n = v_r + v_2, \tag{6}$$

where v_2 is a white Gaussian noise process, independent of v_1. The standard deviation of v_1 is assumed to be 2% of the nominal speed. The standard deviation of v_2 is set to 1 m/s, reflecting the large uncertainty due to blade passing, pitching and tower movements, as well as the fact that spatial variations are not accounted for.

The effective wind speed estimates used in this paper are based on the model and parameter settings provided above.

Figure 1 shows an example of the EWS estimation using the above method. Clearly the nacelle anemometer readings (Vn in the figure) is very noisy compared to the estimated EWS (VeKF in the figure). The main reason for this is that the nacelle anemometer measures over a very small area whereas the turbine "anemometer" measures over at least the rotor area with the result that many small eddies are averaged out.

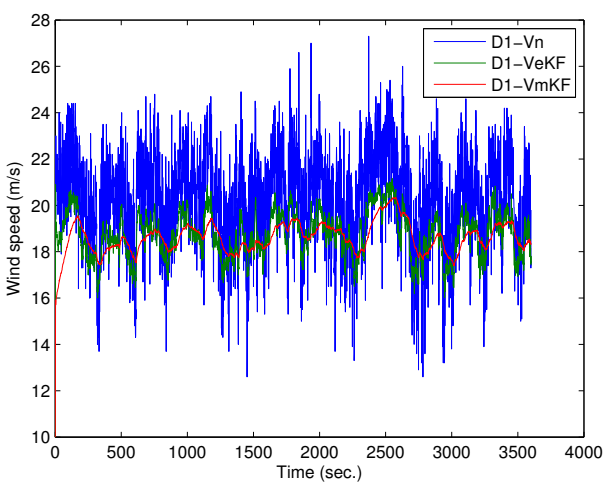

Figure 1: Time series plot of 3600 1 Hz samples of measured nacelle wind speed (Vn), estimated effective wind speed (VeKF) and estimated average wind speed (VmKF).

4 Planning of experiment

As the wind speed in the wake depends on the upwind wind speed and the turbine loading via the thrust coefficient the ideal experiment involves power set point excitation of the wind turbines. This has unfortunately not been possible with the available farm.

Planning the experiment the following is important:

- An average wind direction along the row and with a small standard variation preferable less than 10 deg.
- A mean wind speed and standard deviation which gives good excitation of the thrust coefficient.
- Many samples under similar conditions.

Finding a wind speed that gives good excitation of C_T is not trivial. The thrust coefficient C_T is a function of tip speed ratio λ and pitch angle β. This is also the case for aerodynamic efficiency C_P. This means that in the region of optimal C_P tracking λ, β are constant and so is C_T. Moreover, the operational quasi static dependence of C_T and other turbine variables on wind speed are shown in figure 2. Here it is seen that

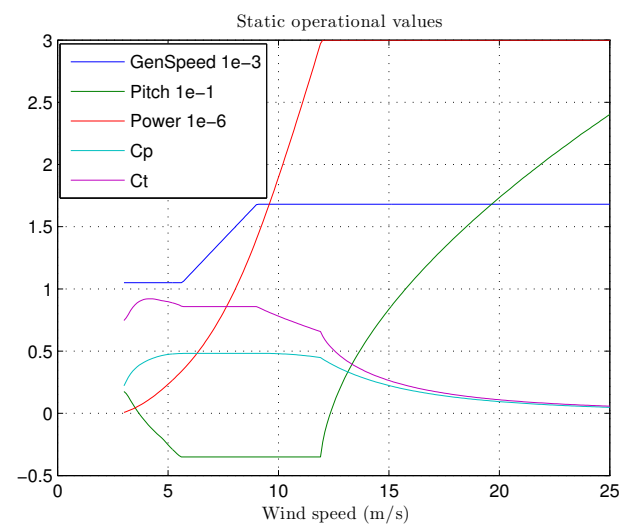

Figure 2: Operational curves for the turbine.

C_T is constant from approximately 6–9 m/s and from 9 m/s it decreases most rapidly from nominal wind speed 12 m/s to 15 m/s due to large pitch variation.

The aim is to estimate the effect of C_T on the wake. Therefore the theoretical effect is useful for planing and assessment of estimated models. Below two widely accepted models are shown. The simplest is the Jensen model [4]

$$c_j = 1 - \frac{C_T}{2\left(1 + \frac{d}{2D}\right)}\ ,\ c_j \triangleq \frac{U}{U_0} \tag{7}$$

where the "wake factor" c_j is defined as the fraction between the wind speed U at a distance d down wind from the upwind turbine and the ambient wind speed U_0. The more complex Frandsen model [5] is given by

$$\beta = \frac{1 + \sqrt{1 - C_T}}{2\sqrt{1 - C_T}}\ ,\ C_T < 1 \tag{8}$$

$$D_W = \left(\beta^{\frac{k}{2}} + \alpha \frac{d}{D}\right)^{\frac{1}{k}} D\ ,\ k = 2\ ,\ \alpha = \frac{1}{2} \tag{9}$$

$$c_f = 1 - \frac{C_T}{2}\left(\frac{D}{D_W}\right)^2 \tag{10}$$

where D_W is the wake diameter. As seen in figure 3 the two models are very similar especially for smaller C_T. As also seen from (7) the Jensen model is affine in C_T.

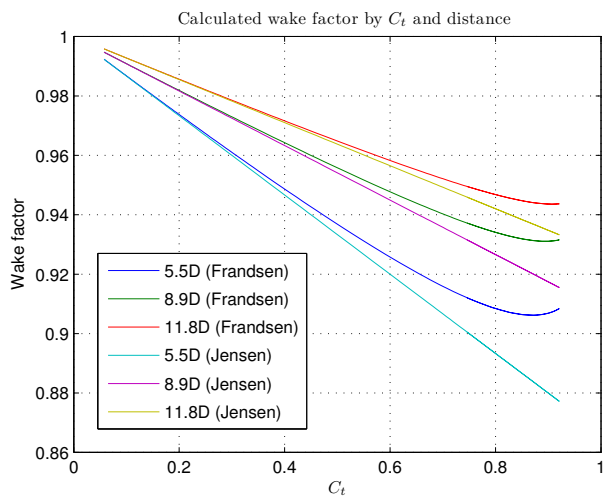

Figure 3: Wake factor by C_T for the turbine.

To select the interesting wind speed for modelling it is necessary to combine the figures 2 and 3 to see the wake factor as a function of the wind speed. This is done in figure 4.

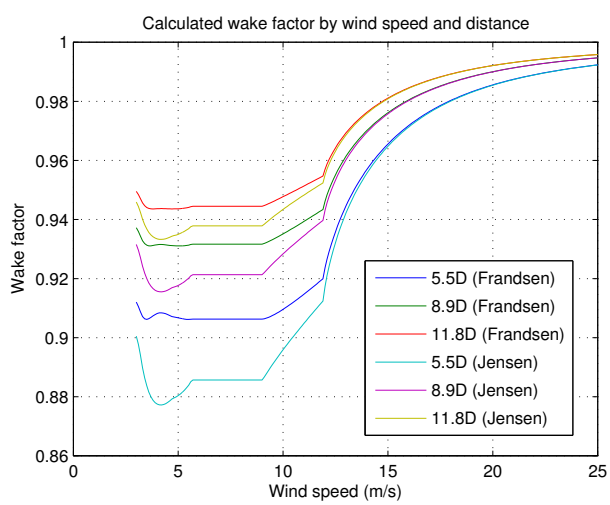

Figure 4: Wake factor by wind speed for the turbine.

From figure 4 several important observations can be made:

- The wake factor is close to 1. For the largest distance the range is approximately 0.94–1 and for the smallest 0.9–1. Therefore data for the smallest distance is preferred.
- For wind speeds below 9 m/s there is no change in the wake factor except below 6 m/s where the turbine is not producing very much.
- The wind speed range 9–15 m/s is the best interval where the largest variation with wind speed occurs.
- The wind speed range above15 m/s is not good as the wake factor is very close to 1.

The optimal wind speed is between 9 and 15 with an average around 12 m/s. It is important to realize that even for these conditions the theoretical wake factor is between 0.9 and 0.96. This is so close to 1, which makes it challenging to capture from experimental data with noise and uncertainty present.

The amount of data available for this investigation is limited. When only data from a narrow range of wind directions can be used it is even more limited. Therefore it has not been possible to meet the ideal requirement to the mean wind speed. The best available data chosen is the four hours show in figure 5 where it is seen that the average wind speed is lower than the ideal case.

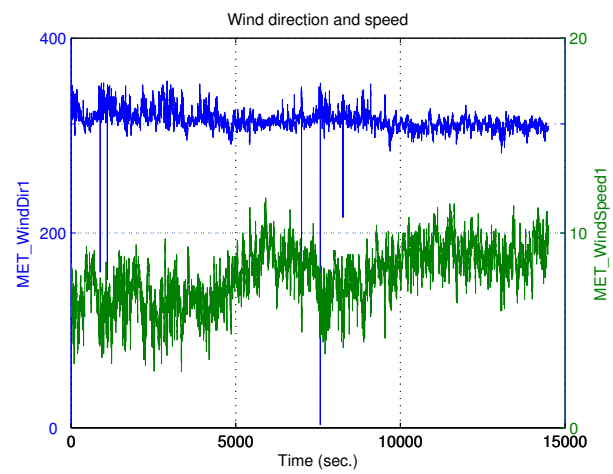

Figure 5: Meteorological mast wind speed and direction. An extra tick mark at row direction 312 degrees is inserted.

5 Static models

In this investigation two different model structures are used to explain the experimental data. For both models the parameters are estimated from data using statistical methods. The parameter estimation is done by manipulating the model to get a simple linear regression equation. A detailed discussion of the statistical aspects are omitted. As the parameters are estimated from data it is really the model structures that are compared.

Notice also that only the simplified situation where the wind direction is along the row is considered here. An extension to other directions will be needed before real application.

5.1 The Multiplicative Model

A straight forward multi wake model is the multiplicative model below where v_n is the EWS at turbine n in a row.

$$v_{n+1} = (1 - kC_{T_n})v_n \Leftrightarrow \tag{11}$$

$$v_{n+1} = \prod_{i=1}^{n}(1 - kC_{T_i})v \tag{12}$$

From (11) it is clear that only information from upwind turbine n is needed for calculating EWS at down wind turbine $n+1$ so in this sense the model is distributed. A consideration with this model is that (12) shows the property that the wind at the end of the row tends to zero as the number of turbines tends to infinity. This does not make sense from a physical point of view, but for a small number of turbines the model can still be a useful approximation.

The parameter k is estimated by linear regression by the reformulation below.

$$v_{n+1} = (1 - kC_{T_n})v_n \Leftrightarrow \tag{13}$$

$$\begin{aligned} &y_n = \alpha x_n \ , \\ &y_n \triangleq v_{n+1} - v_n \ , \ x_n \triangleq C_{T_n} v_n \ , \ \alpha \triangleq -k \end{aligned} \tag{14}$$

5.2 The Additive models

The problem with wake wind speeds tending to zero for a infinite row is not present for the additive models below. This model is also distributed but as seen from (15) it also needs a "farm ambient wind speed". This wind speed can be taken from the front turbine facing the undisturbed flow or perhaps the meteorological mast. To estimate the parameter k in the model (15), it is also rewritten into a form (19) suitable for linear regression estimation of the parameter.

$$v_{n+1} = (1 - kC_{T_n})v - k(v - v_n) \Leftrightarrow \tag{15}$$

$$v_{n+1} = v_n + (1-k)v\delta_n - kvC_{T_n} \ , \ \delta_n \triangleq \frac{v - v_n}{v} \Leftrightarrow \tag{16}$$

$$v_n + v\delta_n - v_{n+1} = k(v\delta_n + vC_{T_n}) \Leftrightarrow \tag{17}$$

$$v - v_{n+1} = k(v - v_n + vC_{T_n}) \Leftrightarrow \tag{18}$$

$$\begin{aligned} &y_n = \alpha x_n \ , \\ &y_n \triangleq v - v_{n+1} \ , \ x_n \triangleq v - v_n + vC_{T_n} \ , \ \alpha \triangleq k \end{aligned} \tag{19}$$

To obtain a more flexible version [7] suggests a model with two parameters which is shown below where it is also turned into a linear regression version. In (23) k and k' are regarded as individual parameters to be estimated.

$$v_{n+1} = v_n + (1-k)v\delta_n - kvC_{T_n} \Leftrightarrow \tag{20}$$

$$v_{n+1} = v_n + k'v\delta_n - kvC_{T_n} \ , \ k' \triangleq (1-k) \Leftrightarrow \tag{21}$$

$$v_n - v_{n+1} = kvC_{T_n} - k'v\delta_n \Leftrightarrow \tag{22}$$

$$\begin{aligned} &y_n = \alpha_1 x_{1,n} + \alpha_2 x_{2,n} \ , \\ &y_n \triangleq v_n - v_{n+1} \ , \ x_{1,n} \triangleq vC_{T_n} \ , \ x_{2,n} \triangleq v\delta_n \ , \\ &\alpha_1 \triangleq k \ , \ \alpha_2 \triangleq -k' \end{aligned} \tag{23}$$

6 Results

6.1 Averaging by direction

To see the effect of wind direction on the wake models the 1 sec sampled data are first grouped in 10 degrees intervals with the midpoints 290, 300, ..., 340 where the row direction is 312. The used wind direction shown in figure 5 is taken from the meteorological mast. As this is very spiky and noisy it has been low pass filtered with the bandwidth 1/60 Hz both forward and reverse to avoid phase lag. Some spikes remain in the filtered direction even after this procedure. The results, of averaging by filtered direction, are seen below including 95% confidence intervals. Clearly, there is a decay in wind speed from upwind turbine number 8 to most down wind turbine number 1. This effect is only clear for the wind directions close to the row direction 312 and here the confidence ranges are also the smallest.

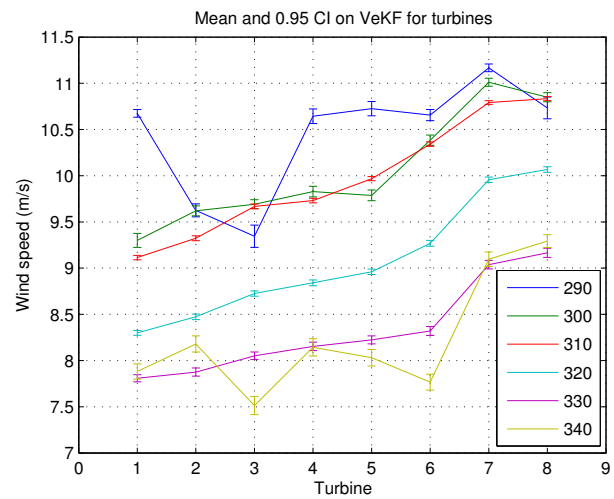

Figure 6: Average EWS by turbine and direction. The wind direction is from right (turbine 8) to left (turbine 1).

6.2 Estimating parameters

For comparison the parameter k for the multiplicative and the two parameter models, can also be found in the Jensen model (7) where it is given by

$$k_J = \frac{1}{2(1 + \frac{d}{2D})} \tag{24}$$

Using the experimental data, the parameters have only been estimated for the direction range closest to the row direction 312 which is then 305 to 315 degrees. The results are seen in table 1 together with the corresponding parameter (24) from the Jensen model.

Model	$\hat{k}$	$\hat{k}'$
Jensen	0.13	
Mult	0.034	
Add One P	0.127	
Add Two P	0.037	0.031

Table 2: Parameter estimates for the models.

The parameter k is here estimated to 0.034 and 0.037 for the multiplicative and the two parameter models respectively.

This gives a less pronounced wake and does not really validate the Jensen model. The second parameter in the two parameter model k' is estimated to 0.031 which does not fit well with the one parameter model where $\widehat{k'} + \hat{k} = 1$ as this sum is 0.068 for the estimates.

The resulting curves are shown in figure 7 together with the data. Clearly the additive model with only one parameter does not fit the data. Including an additional parameter in the additive model gives a good fit. However, the best fit for these eight turbines is obtained by the multiplicative model.

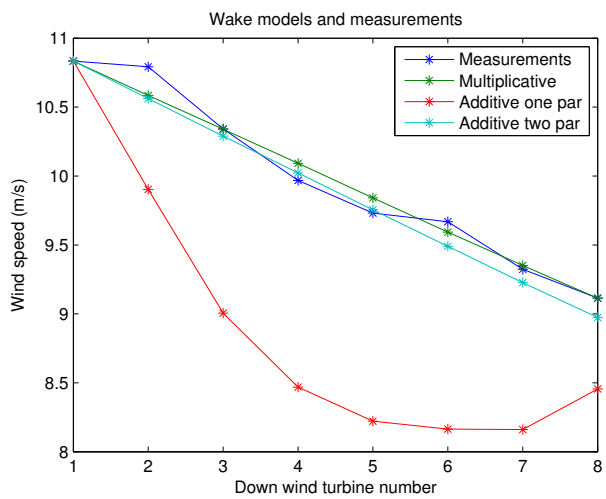

Figure 7: Comparing wake models. The results are only based on samples with directions between 305 and 315 which amount to 6568. Notice that here the turbine numbering is reversed compared to figure 6

7 Conclusion

In this paper wake models for multiple wakes are developed. The effective wind speed measured by the turbines themselves are used for the modelling which is considered important. This effective wind speed is obtained using an extended Kalman filter based on simple models for the wind turbine and the wind speed. After finding the best experimental conditions, four hours of 1 Hz data was selected from a full scale commercial wind farm where the measurement was taken from eight turbines in a row downwind. Simple model structures explaining the wake wind speed from the upwind turbine effective wind speed and thrust coefficient was developed. One of these can be formulated such that the wake at one turbine can be explained only by information from its neighboring upwind turbine. The other model structure also needed the farm ambient wind speed e.g. obtained from front turbines or a meteorological mast. This is useful for e.g. distributed control in a wind farm. Based on data the parameters in these models were estimated. Both model structures fitted the data well but did not really verify the well known Jensen model [4]. Also it is shown that the wake is most significant within approximately ± 20 degrees.

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