ANALYSIS OF TWO ONSHORE WIND FARMS WITH A DYNAMIC FARM CONTROLLER

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Abstract

Coordinated or cooperative control of wind farms can increase power output reducing cost of energy (COE) per area. The increase in production depends upon wind conditions, terrain characteristics and wind farm layout. This work develops an assessment methodology for identifying potential wind conditions where coordinated control can increase farm power output. Average normalised power across all directions, average relative power with reference to a specified turbine and average relative efficiency with respect to the turbine producing maximum power were used for identifying the negative impact of wakes on power output.

A dynamic farm controller is presented that exploits the benefits of reducing power of the upstream turbine(s) for increasing overall farm production. The dynamic controller uses a modified version of the Jensen model for wind speed deficit calculation. This model calculates the wake decay coefficient on a turbine by turbine basis. The decay coefficient varies according to turbulence intensity inside the farm. Particle Swarm Optimisation (PSO) is used for selecting an optimum set of turbine coefficients of power (*Cp*).

The assessment methodology and farm controller were applied to data from two operating onshore wind farms to determine the benefits of coordinated control. The dynamic farm controller can increase power production up to 10% when compared to the conventional greedy control. The modified Jensen model accurately predicted the wind speed deficit in most of the cases. The case study farms were optimised in under 5 seconds on a simple computer. This makes the dynamic controller very suitable for online real time operations.

Keywords: *Wake losses, wind farm coordinated control, dynamic farm controller, modified Jensen model, farm power maximisation.*

1. Introduction

Wind energy is the fastest growing renewable source of energy. Achieving wind energy targets and to make it competitive with conventional sources of energy require reduction in Levelised Cost of Energy (LCoE). Therefore, wind turbines are installed together in clusters to take advantages of economy of scales, obtaining higher energy production reducing the installation and interconnection costs as well as operation and maintenance costs [1]. However, installing turbines together creates aerodynamic interactions between these turbines called wake effects. Wakes can reduce power production of shadowed turbines up to 40% [2]. Wakes not only reduce the farm output but also increase turbulence intensity inside the farm. This can increase fatigue loads up to 80% [3].

The severity of wake effects depends upon wind conditions and farm topology. When the spacing between turbines is low, wake impacts are high. Similarly wind direction and speed also has impact on power losses due to wakes. An assessment methodology is presented in this research for quantifying the wake power losses. This assessment methodology is validated with data from two case study wind farms.

A possible solution for diminishing wake effects is to install the turbines as far from one another as possible but due to space and economic constraints, it is impossible to completely

diminish these interactions as wakes can prevail up to 20 km [4].

Another way for reducing negative impacts of wakes on farm power output is to use a coordinated control of wind turbines [4]. A dynamic farm controller with a coordinated control approach has been developed and used for maximising the farm power output. This controller has two integral parts – a wind deficit model and an optimiser. This work develops a modified version of the Jensen wake model for wind speed deficit calculation [5, 6]. The wind deficit model is evaluated with the case study wind farms. PSO is used for selecting the optimum production of individual winds turbines which can increase overall farm production [7].

This paper is organised as follows. Section 2 describes the methodology applied in this paper. Section 3 details the case study wind farms and data filtering. Section 4 presents results and analysis. The conclusion and some future work is presented in section 5 and 6 respectively.

2. Methodology

This section describes the assessment methodology and dynamic farm controller developed in this study. Section 2.1 describes the assessment methodology. Section 2.2 details the dynamic farm controller.

2.1. Assessment

As described in section 1, wakes can negatively impact farm power output. The severity of this impact depends up on farm layout and wind conditions. The proposed assessment methodology is used for quantifying negative impacts of wakes and identifying wind conditions where coordinated control of the farm can increase overall farm output. The methodology comprises of the following three steps.

First average normalised power is calculated in each direction. Power is normalised between 0 and 1. Normalisation is performed for the following reasons.

1. Turbines have different capacities. Normalising the power production within the same limits make the comparison easy.
2. Powers are amplified as can be seen in equation (1). Turbine producing minimum power at a particular instant has zero normalised power as the numerator in

equation (1) becomes zero. The denominator amplifies the normalised power.

$$Avg. Norm\ Pwr = Avg \left(\frac{Power(i) - a}{(b - a)} \right) \quad (1)$$

where

$a = \min(Power(1), ..., Power(n))$

$b = \max(Power(1), ..., Power(n)$

This is used for identifying areas where wakes produce severe power losses on shadowed turbines. Usually the crosswind spacing is lesser than the downwind spacing [4]. Therefore, the farm output is affected more in some wind directions than others. The average normalised power presents a comparison of wakes impact on power output in all directions.

Once wind conditions where wakes adversely affect the farm are identified, average power relative to the first turbine (A1 or B1) is calculated for all the turbines in the array as shown in equation (2). (*Power (i)*) is the power of turbine under consideration and (*ref turbine*) is the turbine with reference to which the relative power is calculated. This shows the impact of wake on average power production of each turbine.

$$Avg\ Rel\ Pwr = Avg \left(\frac{Power(i)}{Power(ref\ turbine)} \right) (2)$$

The final step of assessment methodology is to calculate relative efficiency of the turbines with respect to the turbine producing maximum power. This means that for each record, the turbine producing maximum power will have relative efficiency of 1. Average relative efficiency shows the performance of turbines relative to the turbine producing maximum and can be found with equation (3).

$$Avg\ Rel\ Eff = Average \left(\frac{Power(i)}{b} \right) \quad (3)$$

2.2. Dynamic Farm Controller

Traditionally wind turbines in a wind farm are controlled individually with a greedy control. Each turbine maximises its own power, neglecting the wake effects on shadowed turbines [4, 8, 9]. This control strategy does not yield maximum farm power production in certain wind conditions as identified by the assessment methodology. Coordinated control of the turbines can increase the farm production in these wind conditions. Curtailing the upstream

turbine(s) leaves more wind for production of downstream turbine(s). If this control is applied in such a way that decrease in upstream turbines' production is less than increase in downstream turbines' production then their combined production will increase.

The concept of coordinated control was first presented by [6]. The work in [9] used axial induction factor for controlling wakes and increasing farm production. Previous studies in [4, 10-15] have also explained the benefits of coordinated control. These studies suggest that the farm controller should be fast and accurate.

The dynamic controller developed in this work has two integral parts – a wind deficit model and an optimiser as shown in Figure 1. The term dynamic here means that the controller can be used online dynamically for optimising power production of a wind farm. The wind deficit model is used for evaluating different power settings of turbines. The optimiser searches for optimal individual turbine settings resulting in the maximum combined output.
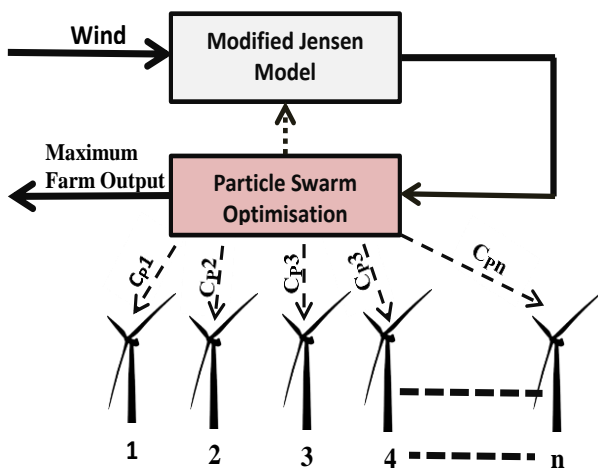

Figure 1: Dynamic Wind Farm Controller Schematic Diagram

2.2.1. Control Strategy and Optimisation

The control strategy, objective function and optimisation procedure were presented in [7]. The objective function is to minimise the difference between farm output power assuming there are no wakes (theoretical maximum possible for a given wind speed) and the power produced in presence of wakes as shown in equation (4). PSO is used for optimising this objective function [7].

Obj Function
$$= Min(Power_{no\ wakes} - Power_{with\ wakes})\quad(4)$$

2.2.2. Modified Jensen Model

This work exploits the Jensen model [5, 6] for wind speed deficit calculation. The Jensen model is practical as long as the mean production rather than velocity field is area of interest [6]. However, the simplified assumptions such as ideal flow of wind and constant wake decay make it unable to predict wind deep inside the farm correctly [14]. In some cases, the model can even result in negative speeds in wakes making the model invalid for near wake regions.

The Jensen model assumes that wake spreads linearly behind the turbine with a constant decay coefficient. The downstream deficit in wind speed can be found with equation (5). r and k can be found with equation (6) and (7) respectively [5, 6]. Table 1 gives a description of all the variables used in this section.

$$u = u_0\left[1 - \left(\frac{1-\sqrt{1-C_T}}{\left(1+\frac{kx}{r_0}\right)^2}\right)\right]\quad(5)$$

$$r = r_0 + kx\quad(6)$$

$$k = 1/[2\ ln(z/z_0)]\quad(7)$$

Turbines affected by wakes experience more turbulent wind, changing the atmospheric

Table 1: Variables in the modified Jensen Model

C_T	Coefficient of Thrust
I_+	Wake Added turbulence intensity
I_0	Free stream turbulence intensity
I_u	Longitudinal turbulence intensity
I_{wake}	Wake added Turbulence intensity
k	Wake Decay coefficient
r	Radius of spread of the wake
r_0	Blade length
u	Wind Speed in the wake
u_0	Free Stream Wind Speed
x	Distance at which wake is calculated
x_n	Length of the near wake
z	Hub height of wake generating Turbine
z_0	Surface Roughness length

stability and hence surface roughness length. Therefore, k shall have different values inside the wind farm. Different approaches have been used for adjusting the value of k to match the wind speed reduction in wakes. Two different values of k have been used in [16]. One value is used for free stream wind and the other one for all the downstream turbines under wake effects. Linear regression is used in [14] for obtaining the value of k matching the results of SOWFA. Discrete bins of turbulence intensity were used in [17] for determining the value of k to match the values provided by WindPro software. The work in [18] evaluates the value of k for matching real time data under different wind conditions.

The model developed in this work adjusts the value of k according to a correction factor. This correction factor is based on the turbulence intensity inside the wind farm. Wakes increase turbulence intensity inside the farms [14]. This increases rate of dissipation of wakes resulting in higher values of k According to [16] the longitudinal turbulence intensity is specified by equation (8).

$$I_u = \frac{1.0}{ln(z/z_0)} \qquad (8)$$

Replacing equation (8) in (7)

$$k = I_u / 2 \qquad (9)$$

Wake added turbulence can be found with equation (10) as given in [16].

$$I_+ = 5.7 * C_T^{0.7} * I_0^{0.68} * (x/x_n)^{-0.96} \qquad (10)$$

Turbulence Intensity in the wake can now be found with equation (11) [16].

$$I_{wake} = \sqrt{I_+^2 + I_0^2} \qquad (11)$$

For isotropic conditions, lateral, vertical and longitudinal turbulence intensities are equal therefore I_U is one third of the total turbulence intensity as given in following equation (12).

$$I_u = \frac{I_{wake}}{3} \qquad (12)$$

This value of I_u is used in equation (5) for finding the actual value of k inside the wind farm. Wake expansion still remains linear but the value of k changes on turbine by turbine basis in the wind farm.

The model determines if a shadowed turbine is under full, partial or no wake effects. Multiple wakes are superimposed as given in [6]. The model uses a predetermined value of k for the free stream conditions. This value depends upon turbulence intensity, terrain characteristics and wind conditions.

3. Wind Farm Case Studies

Case-study farms are Brazos Texas, USA (labelled Wind Farm A) and another farm in France (labelled Wind Farm B as details of this wind farm cannot be disclosed due to commercial interests). Figure 1 represents the layout of the Brazos wind farm. The row A1 – A7 from Brazos, shown in Figure 1, is considered for analysis as the layout is similar to Farm B. It can be seen that the first 5 turbines are installed in a straight line. The last two turbines are not completely in line with the first 5 turbines but in line with each other. Terrain of both the farms is also very similar. Detailed information about the Brazos wind
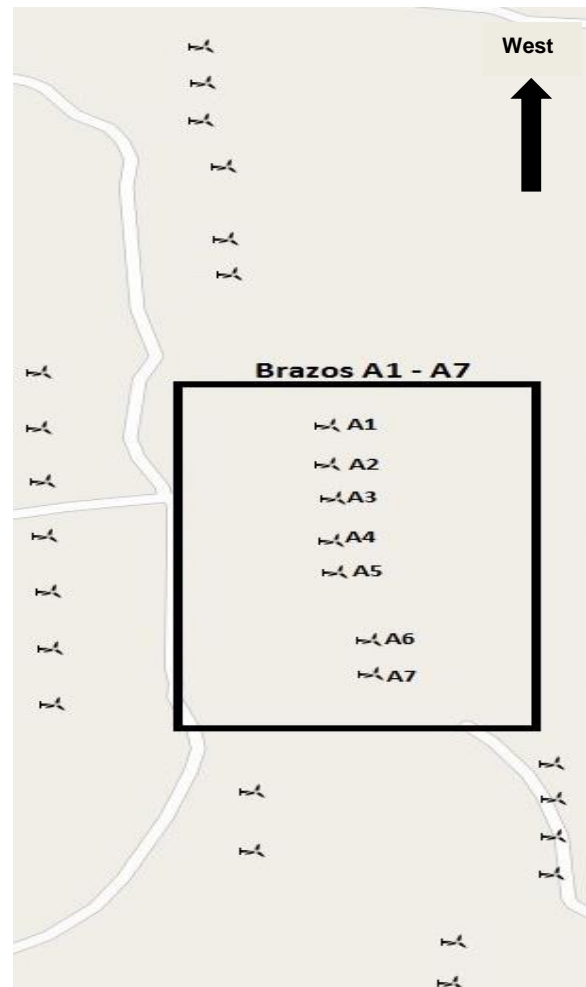

Figure 2: Layout of the Brazos Wind Farm (A1 - A7) [22]

farm and terrain characteristics can be found in [18].

The Brazos data is SCADA data from 2004 – 06 from the ReliaWind project [19]. Farm B SCADA data from 2013 -15 was used in this study. Details of Brazos row A1– A7 and the turbine characteristics are presented in Table 2.

Table 2: Brazos 1MW Turbine Characteristics [21]

Capacity	1 MW
Max Cp	0.405
Hub Height	68 m
Blade Length	29.5m
Rated Wind Speed	12.5 m/s
Cut-in Wind Speed	2.5 m/s
Cut-off Wind Speed	24 m/s
A1–A2–A3-A4-A5 separation	2D
A5 – A6 separation	3.5D
A6 – A7 separation	2D
Wind direction has been rotated by 90° to match the data of Farm B	

3.1 Data Filtering

A database was created from the SCADA data of the wind turbines. Records where data for all the turbines was available and where the turbines were producing at full capacity were used in analysis. Turbine power and wind direction signal from the SCADA data were used.

A wind speed bin of ±0.5m/s was used. The directional bin starting from $±20^O$ refined to $±1^O$ was analysed. It was observed that a bin of $±5^O$ captures most of the wake affected area. Studies in [20] suggested a directional bin of $±10^O$ for offshore farms. Onshore, higher surface roughness causes the wind speed to recover quickly. Therefore, the directional bin was kept at $±5^O$. Wind direction for Brazos was rotated by 90° to match the data of Farm B.

4. Results and Analysis

The analysis for 5m/s – 14m/s were conducted. Results for the extreme cases at 8m/s are presented here.

4.1 Assesment

The assesment methodology was applied to data from both the wind farms. Figure 3A and Figure 3B shows the average normalised power
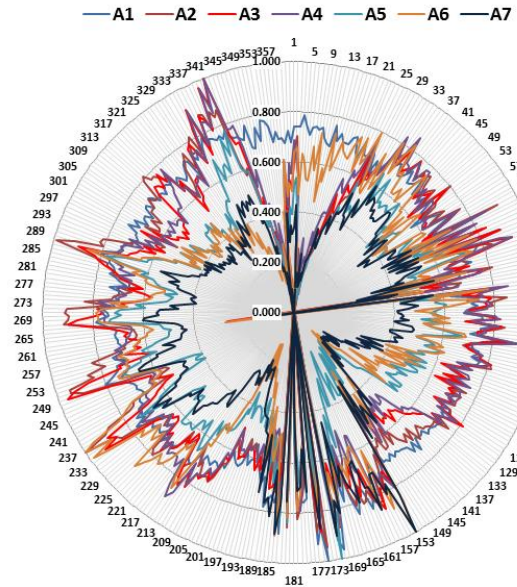

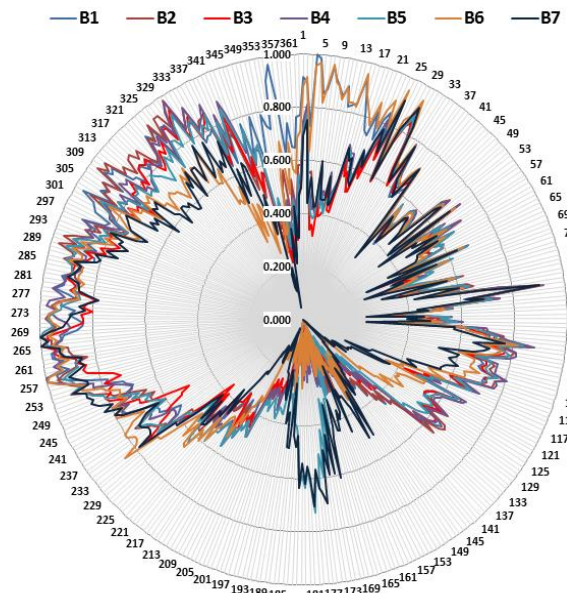**Figure 3A: Average Normalised Power at 8 m/s for Brazos A1 - A7**

Figure 3B: Average Normalised Power at 8 m/s for Farm B B1 - B7

in each direction at 8m/s for the Brazos and Farm B respectively. It can be seen that the power losses due to wakes are very high in 0° $±40^O$ and 180° $±40^O$.This is when the wind is completely or almost parallel to the turbine array. This was the case for all the wind speed bins. This step of the assesment methodology shows the severity of wake effects on power production in different directions.
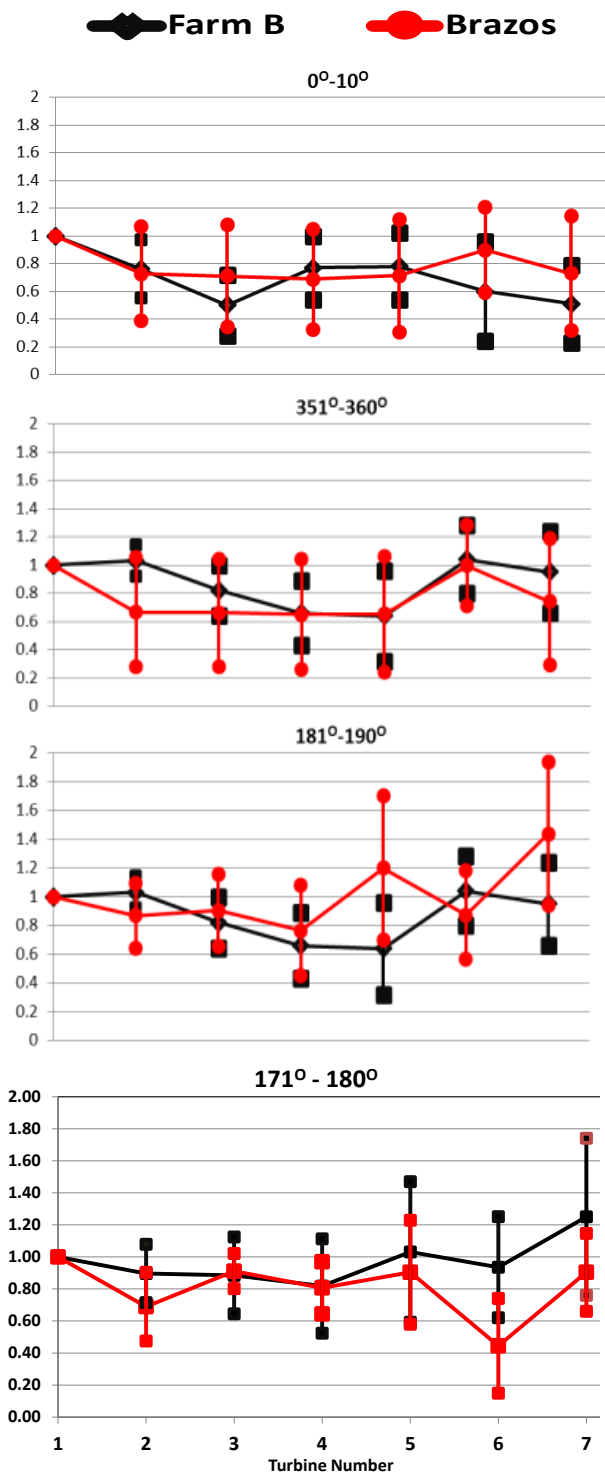
Figure 4: Average relative power at 8m/s in four directional bins

Figure 5: Average relative efficiency at 8m/s in four directional bins

The next step is to quantify these wake power losses by calculating relative average power in each directional bin. with respect to turbine A1 and B1 (randomly choosen).This gives the average power drop for different turbines. Figure 4 compa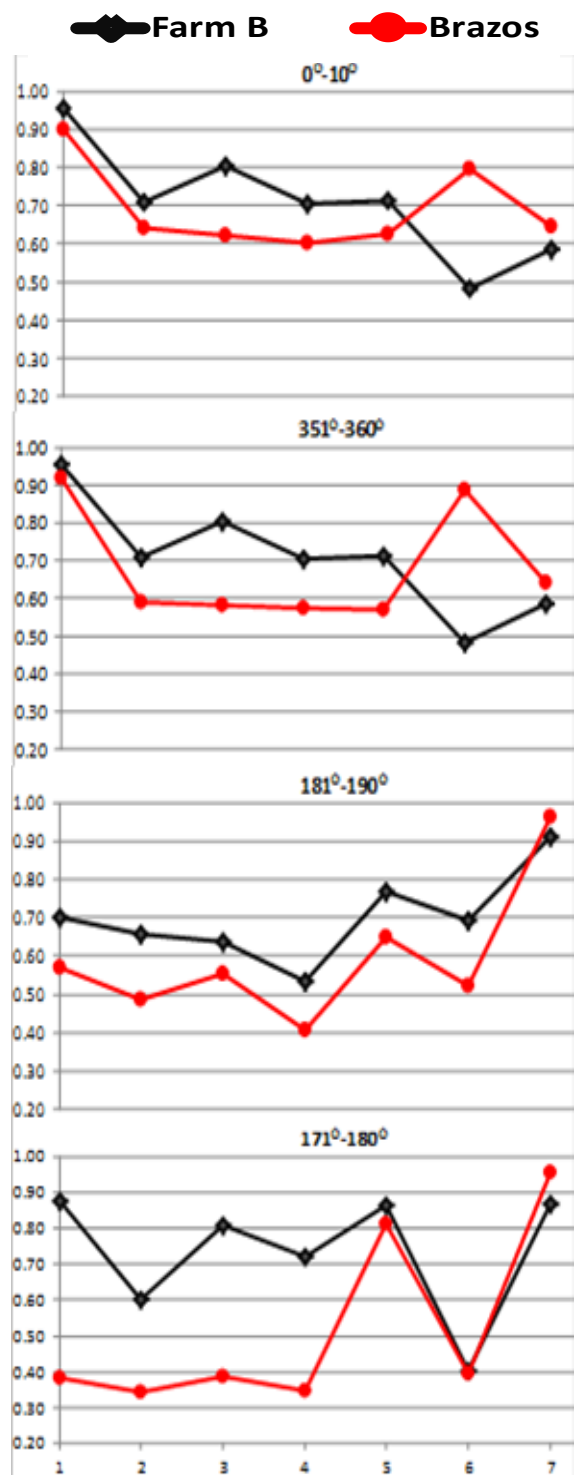res the relative average power in the two farms at 8m/s in four different dirrectional bins. The line bar represents standard deviation of the data. High spread of data shows the stochastic nature of wind. It can be seen that power losses can be as high as 55% in the worst conditions.

Figure 5 shows a comparison of the two farm in terms of average relative efficiency for four different directional bins. This shows the performance of turbines with respect to each other. The relative efficiency could go as low as 40%. This shows that some of these wind turbines produces very low in certain wind conditions.

The assessment methodology has identified wind directions $0^O \pm 40^O$ and $180^O \pm 40^O$ i.e. wind flowing parallel to the turbine arrray affects the power production badly. These wind conditions were further investigated with average relative power and average relative efficiency of the turbines. Power losses due to wakes can be as high as 55% in the worst case. The relative efficiency of some of the turbines can go as low as 40%. Main reason for these huge power losses is the very short spacing between the turbines and peculiar layout of the turbine array.

4.2. Dynamic Farm Controller

This section first validates the modified Jensen model with data from Farm B. This model is then combined with PSO and applied to the data to show the increase in farm production compared to the state of the art greedy control.

4.2.1. Modified Jensen Model

Three days wind data set was chosen for evaluating the wind deficit model. During this period the wind predominantly flew parallel to the turbine array. That's why this data was chosen. The actual wind speed at the turbine was determined through the power signal from the SCADA data. The power signal is much more reliable as compared to the wind speed signal.

Figure 6 shows the comparison between the actual and predicted wind speed by the modified Jensen model for turbine B2 – B5 (Farm B). The difference between actual and predicted wind speed is also shown. It can be seen that the model accurately predicts the wake affected wind speed. A difference of ±0.5m/s is acceptable as long as the purpose is farm control. It shall also be noted that the model is acceptable for developing control strategies as long as it is underpredicting the wind speed on shadowed turbines in a given limit. However, if it overpredicts the wake affected wind speed then the farm controller will result in false increase in power production. This can result in lower farm

production in real time operations as compared to the conventional greedy control. It was noted that in very few cases the model overpredicts the wind speed more than ±0.5m/s. The model
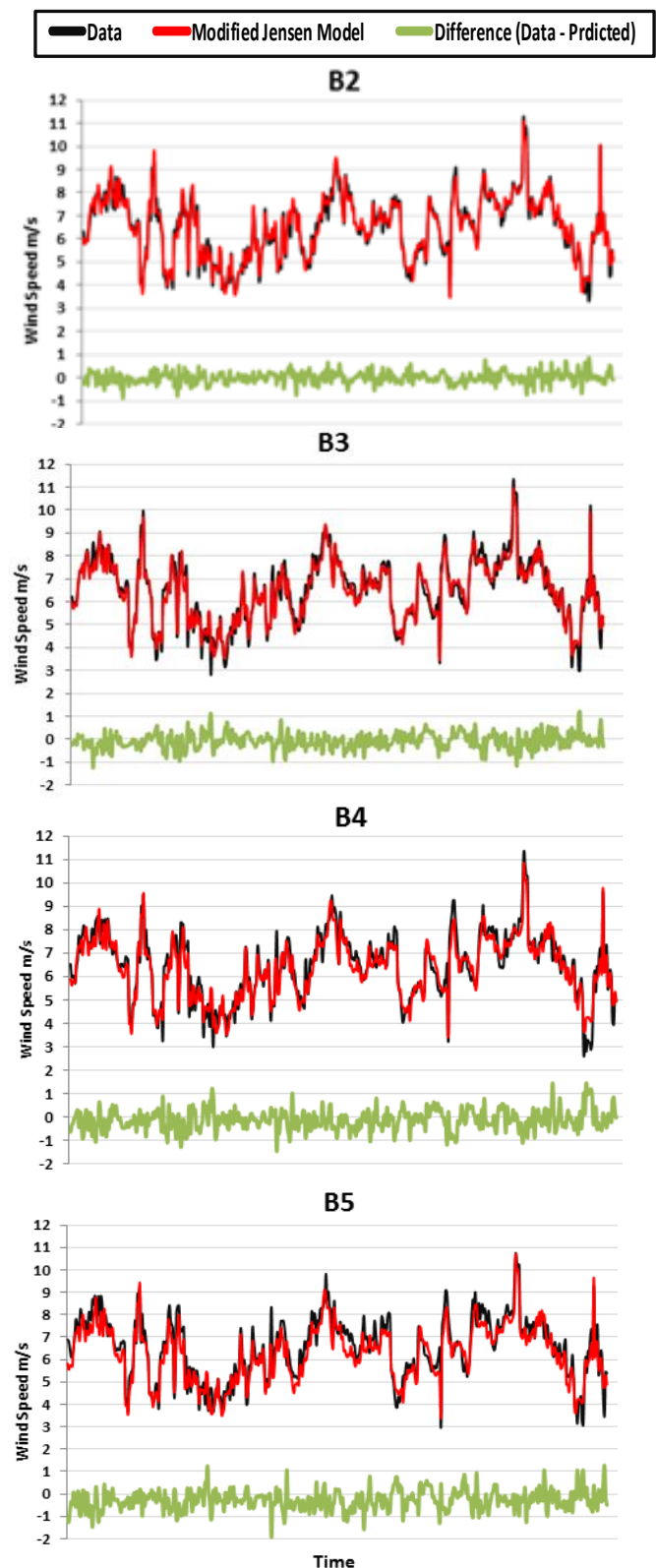

Figure 6: Comparison of actual and predicted wind speed for 3 continuous days for turbines B2 – B5 (Farm B)

is accurate and fast processing. This makes the modified Jensen model very suitable for developing farm control strategies.

4.2.2. Optimisation

The modified Jensen model was combined with PSO for optimising the objective function in equation (4). It is already shown in the previous section that the wind deficit model can accurately predict the wind speed deficit. The PSO based control strategy is detailed in [7]. Figure 7 shows application of the dynamic farm controller on one instance of data. Figure 8 shows the C_P values suggested by the dynamic farm controller and the C_P values used by the conventional greedy control. Figure 9 shows comparison of turbines' power produced with the two control strategies. It can be seen that the power of head turbine has been reduced by almost 400 kW. The last turbine always operates at the maximum C_P with a greedy approach. Reduction in power of the upstream turbines resulted in an increase of up to 10% with the case study wind farms compared to state of the art. The control algorithm takes less than 5 seconds to complete on a simple computer. Speed and accuracy are the two main strengths of the farm controller proving that it can be used online (dynamically) for farm control. It can accurately optimise the farm power within a few seconds making it very suitable for online control in the field.

5. Conclusion

This work presented an assessment methodology for deployment of a dynamic farm controller. This was illustrated using two operating onshore farms as case-studies. Average normalised power across all directions was used for identifying potential wind conditions where farm control can be used. Relative average power and relative efficiency were then used to show how severely wakes can impact production and efficiency of shadowed turbines. The results shows that wakes can reduce the power of shadowed turbines up to 55%. Efficiency of some of the turbines was reduced up to 40% in certain wind conditions. The analysis show that a wind speed bin of ± 0.5 m/s and directional bin of $\pm 10^{O}$ is suitable for the case study farms.
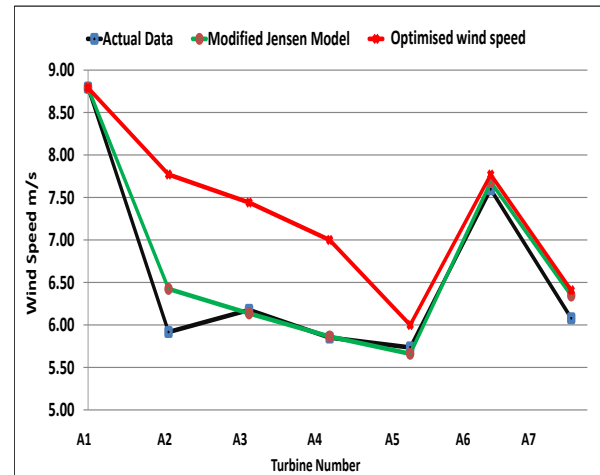

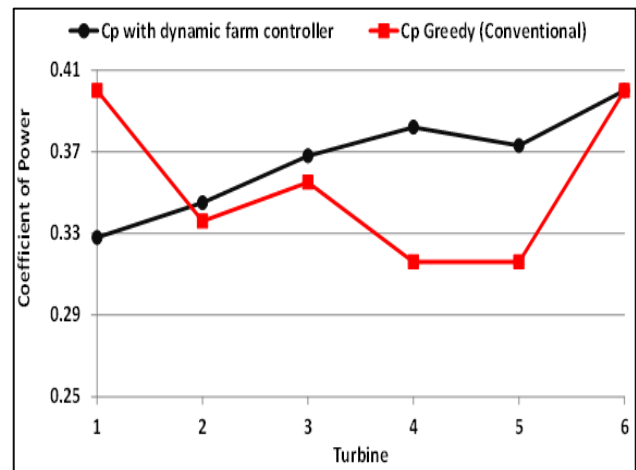**Figure 7: Comparison of actual with predicted wind speed by the Jensen model and modified Jensen mode (Farm B)**

Figure 8: C_P of first six turbines with conventional control and the proposed dynamic controller (Farm B)
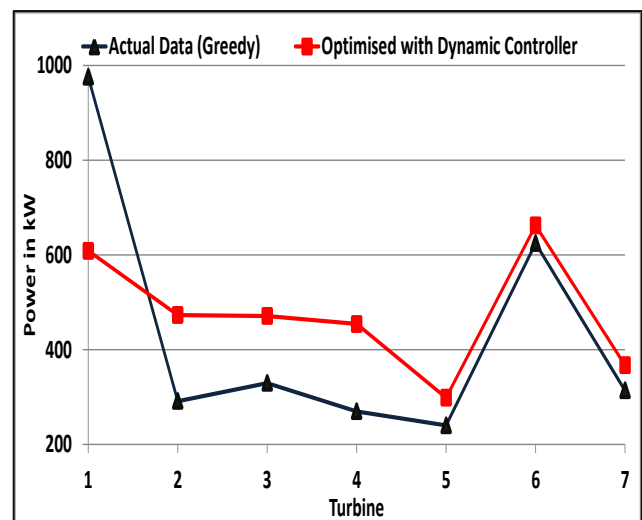

Figure 9: Actual power with power produced with the dynamic farm controller (Farm B)

A modified Jensen model was developed which calculates the wake added turbulence intensity for deriving the value of wake decay coefficient. This model was first validated with real time data from Farm B and then combined with PSO to form a dynamic farm controller based on coordinated control of the wind farm. Based on the two case studies presented, the dynamic farm controller can increase farm production up to 10% compared to the current state of the art control, completing the optimisation in less than 5 seconds making this suitable for online field use.

6. Future Work

The modified Jensen model will be validated with data from 2 dimensional wind farms. Performance of this wind deficit model will be compared to high fidelity CFD models. The farm controller will be extended for multi-objective optimisation considering power production and loads experienced by the turbines.

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