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Dynamic Wind Farm Controller

Tanvir Ahmad*[1], Peter C. Matthews, Behzad Kazemtabrizi, Christopher J. Smith
School of Engineering & Computing Sciences, Durham University
Durham, UK
[1]tanvir.ahmad@durham.ac.uk

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Abstract - This work presents a dynamic wind farm controller for maximising power output of a wind farm. The controller uses a coordinated control approach where the output of the upstream turbines is varied to minimise wake effects on the downstream turbines. The speed deficit due to wakes is calculated using a modified version of the Jensen wake flow model. This model gives the wind speed at different locations in the wind farm. Particle Swarm Optimisation (PSO) is used to generate different sets of coefficients of power (C_P) for all the turbines and select the one which results in maximum farm output. The Brazos wind farm is used as a case study. The controller optimises a row of seven wind turbines in less than 5 seconds and increases the farm output by 9%. High computational efficiency and accuracy make the proposed controller very suitable for practical implementation in industry.

I. INTRODUCTION

Clustering wind turbines together can take advantage of economies of scale. However, this creates aerodynamic interactions among them in the form of wake effects. Due to wakes a wind farm will produce less power than a similar number of isolated turbines. Studies in [1, 2] suggest that power losses due to wakes can reach up to 40%. Wakes also increase fatigue loads on downstream turbines by up to 80% [2]. One way to reduce the negative impacts of wakes is to place the turbines as far away from another as possible. However, wakes can prevail up to 20 km. Even with an optimised farm layout an average 8% power losses occur onshore and 12% offshore [3]. This increased loss offshore is due to the wind taking a longer distance to recover in wakes because of less surface roughness of the sea water.

Conventionally wind turbines in a wind farm extract maximum possible energy from the wind without considering the wake effects on downstream turbines – known as the greedy approach. This will not always result in maximum farm output. Coordinated control of the wind farm can increase farm power in certain wind conditions. If the power output is optimised in such a way that the reduction in power of the upstream turbines' is less than the increase in power of the downstream turbines – the total farm power will be increased. This coordination can be achieved with a farm controller which chooses an optimised power combination of the turbines.

The concept of coordinated control was first presented in [4]. Studies in [3, 5-10] detail the benefits of coordinated control. These studies suggest that the whole control process has to be very fast. The farm controller requires a wind deficit model which is used for producing different sets of outputs of the turbines. An optimiser is then used to select the set of powers which results in maximum collective power. Therefore, both the wind deficit model and optimiser should have high processing speed. The optimiser should also have low computational overheads using minimum number of trials or sets of power for reaching an optimum value. Low number of trials assures fewer calls to the wind deficit model. This is of great importance as wake models can be computationally expensive. A high processing optimiser with low computational overheads makes sure that enough time is left for execution of the wind deficit model.

The aim of this work is to develop a fast processing farm controller with enough accuracy for maximising the total wind farm output with realistic assumptions. This controller is used online for increasing farm production.

This paper is organised as follows. Section II presents the modified Jensen model. Section III formulates the objective function for optimisation. A description of PSO is given in section IV. Details of the case study wind farm are presented in section V. Results and analysis are given in section VI.

II. THE MODIFIED JENSEN MODEL

The farm controller requires an estimate of wind speed deficit in the vicinity of each turbine. It does not require details of the wake flow. Therefore, the Jensen model can be used for farm control. It is practical as long as the mean wind power rather than the velocity field is area of interest [4]. However, the assumptions such as ideal flow of wind and a constant value of decay coefficient in the whole wind farm make it unable to predict wind deficit accurately deep inside the farm.

This work modifies the Jensen model by applying a correction factor to the wake decay coefficient. This correction factor is based on the turbulence intensity in the vicinity of shadowed turbine. The turbulence model in [11] is used for calculating wake added turbulence. The wake expansion downstream is still linear but the width of wake is not constant.

According to the Jensen model the downstream deficit in wind speed depends upon blade length (r_0), distance at which wake is calculated represented by (x), thrust coefficient of the turbine (C_T) and the wake decay coefficient (k). k gives the spread of wake and depends upon hub height (z), turbulence intensity (I) and atmospheric stability. Radius of the wake spread is given by (r), (u_0) is the free stream wind speed, (u_T) is the wind speed just behind the rotor and (u) is the wind speed at x which could be found with Eq. (1). (z_0) is a constant, which represents surface roughness length which depends on the characteristics of local terrain [4, 12]. The width of the wake and k can be determined with Eq. (2) and Eq. (3).

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

$$r = r_0 + kx \quad (2)$$

$$k = 1 / [2\, ln\, (z / z_0)] \quad (3)$$

The model in [4, 12] uses a constant k for the whole wind farm. Turbines affected by wakes experience more turbulent wind changing the atmospheric stability and hence z_0. Therefore, k should have different values inside the wind farm.

According to [11] the longitudinal component of I can be found with Eq. (4).

$$I_u = {1.0}/{ln(z/z_0)} \quad (4)$$

Replacing Eq. (4) in Eq. (3) produces the actual value of k as given in Eq. (5).

$$k = I_u / 2 \quad (5)$$

Wake added turbulence intensity (I_+) can be found analytically with Eq. (6) [11].

$$I_+ = 5.7 C_T^{0.7} I_0^{0.68} (x/x_n)^{-0.96} \quad (6)$$

(I_0) is the free stream turbulence. The only unknown here is x_n which is the length of the near wake region and can be found in terms of r_0 and C_T [11]. Turbulence intensity in the wake (I_{wake}) can then be found with Eq. (7) [11].

$$I_{wake} = \sqrt{I_+^2 + I_0^2} \quad (7)$$

For isotropic conditions, lateral, vertical and longitudinal turbulence intensities are equal and therefore, longitudinal turbulence intensity is one third of the total turbulence intensity as given in Eq. (8).

$$I_u = {I_{wake}}/{3} \quad (8)$$

This value of I_u is used in Eq. (5) for calculating the value of k inside the wind farm.

The I_u calculated here can be considered as the correction factor for determining the correct value of k. An upper limit is imposed on the value of I_u meaning that after 4th turbine, k remains constant inside the wind farm. This is very much in agreement with the data available from the Brazos wind farm.

III. Control Problem

The total wind farm power is the sum of the individual wind turbines' output. The output of a wind turbine is given by Eq. (9). (ρ) is the air density and (A) is turbine swept area.

$$P_{Turbine} = \frac{1}{2}\rho A u^3 C_P \quad (9)$$

Total wind farm power with N number of turbines is given by Eq. (10), i being the turbine under consideration. Wind speed at turbine i is given by $u(i)$ and the corresponding coefficient of power is $C_P(i)$. The free stream wind speed is assumed to be below rated.

$$P_{With\_Wakes} = \sum_{i=1}^{N} P_{Turbine\ (i)} = \sum_{i=1}^{N} \frac{1}{2}\rho A u(i)^3 C_P(i) \quad (10)$$

If all the turbines are operating in free flow conditions with no wakes and at their maximum $C_{P\,(max)}$, the maximum achievable combined output is given by Eq. (11).

$$P_{No\_Wakes} = \frac{1}{2}\rho A \sum_{i=1}^{N} u_0{}^3 C_{P(\max)} \quad (11)$$

The optimisation problem is to minimise the difference between Eq. (10) and Eq. (11). Ignoring the constant terms - $\frac{1}{2}\rho A$, the objective function becomes as given in Eq. (12).

$$Min(P_{NoWakes} - P_{WithWakes})$$
$$Min[\sum_{i=1}^{N} u_0{}^3 C_{P(\max)}(i) - \sum_{i=1}^{N} u(i)^3 C_P(i)] \quad (12)$$

A detailed description of control problem can be found in [13].

IV. Particle Swarm Optimisation

It was concluded in [13] that PSO outperforms other heuristic techniques in terms of processing speed, computational overheads and uses minimum number of trials to reach an optimum value. Therefore a basic description of PSO is given as following.

PSO was first presented by Russell Eberhart and James Kennedy [14]. The algorithm is inspired by the flocking of birds and the schooling of fish. In PSO, particles are artificial agents but with no individual intelligence. By moving in a swarm they create a collective intelligence which helps them to solve optimisation problems. Each particle is a potential solution to the given problem.

PSO keeps record of each particle's personal best, the best fitness value a particle has achieved so far, and the swarm's global best, the best fitness value for all particles. All particles will move towards global best and their personal best to find the best possible solution [14, 15]. This process is iterative. The local best for each individual particle and swarm's global best is updated each iteration. The velocity of moving towards the solution is set by a specific set of equations. This velocity (V_i) at time (t) depends upon current position ($x_i(t)$), inertia, constants (c_1, c_2), random variables (R_1, R_2), the global best (p_g) and local best values ($p_i(t)$) as show in Eq. (13) and Eq. (14) [14, 15]. The values of these variables depend upon the specific problem under consideration. Each iteration, the swarm gradually builds up a direction and movement towards the optimum value by directing the personal best solutions using global best. The algorithm terminates when the required solution is reached or when number of iterations is completed.

$$V_i(t+1) = R_1 V_i(t) * inertia + c_1 R_2 * \left(p_i(t) - x_i(t)\right) - c_2 R_3 * \left(p_g(t) - x_i(t)\right) \quad (2)$$

$$x_i(t+1) = x_i(t) + V_i(t+1) \quad (3)$$

Detailed description of how PSO is used for coordinated control and a comparison with other heuristic techniques can be found in [13].

V. CASE STUDY – BRAZOS WIND FARM

The Brazos wind farm is an onshore wind farm with more than 150, 1MW turbines. It is located in Texas, USA. A row of seven wind turbines is used for analysis in this study. The layout of this row of turbines is shown in Fig. 1. Characteristics of the turbines and details of turbine placement are given in Table 1. Two years of Supervisory Control And Data Acquisition (SCADA) data 2004 -2006 was used[16].

The power, wind speed and wind direction signals were used in this study. It can be seen in Fig. 1 that turbine 6 and 7 are not completely in line with turbines 1-5. Therefore, when wind direction is parallel to the turbine array, turbine 6 will be under partial wakes from the upstream turbines. These partial wakes are superimposed with free-stream wind speed so that turbine 6 will have more wind speed as compared to turbine 2-5. Turbine 7 is then under full wakes from turbine 6.

Fig 1. Row of 7 Turbines from Brazos Wind Farm [17]

Table 1: Brazos 1MW Turbine Characteristics [18]

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

VI. RESULTS AND DISCUSSION

The dynamic farm controller was used for optimising the case study wind array in different wind conditions. Results for the most extreme case are presented here, meaning that the wind flow is parallel to the turbine array and that turbine are in full wakes.

Fig 2 shows the wind speed predicted by the modified Jensen model and optimised with PSO. It can be seen that the wind speed inside the wind farm was predicted accurately. It can also be seen that just by reducing the power of the upstream turbines the downstream turbines have more wind for production.

Comparison of power production of greedy control and coordinated control is presented in Fig 3. The power of first turbine is reduced by almost 400 kW but this leaves enough power for downstream turbines for increasing their combined production. It can be seen that an overall increase of up to 9% was achieved by the dynamic controller. All this process was completed in less than 5 seconds.

Table 2 presents a comparison of all the optimisers. It can be seen that PSO, Genetic Algorithm (GA) and Simulated Annealing (SA) all produces the same solution which is 98.5% of the global optimum. Considering the complexity of the problem, this is a very good result.

PSO outperforms other optimisers in all other aspects. It takes the shortest time for processing by using minimum number of trials and hence number of calls to the wind deficit model. GA has high processing speed but the number of trials is 14 times greater than the PSO result. The overall increase in production over the conventional control is 9% in this case.

Fig 4 shows the movement of some random PSO particles towards optimum *Cp* values. It can be seen that PSO reduces the *Cp* of upstream turbines for increasing overall production of the farm.

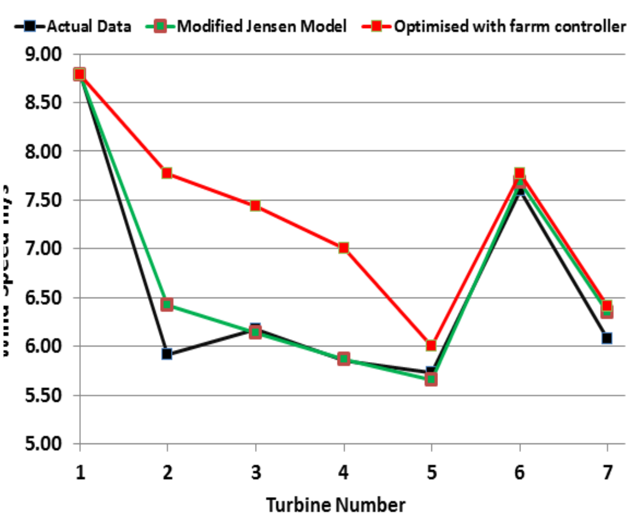

Fig 2: Wind Speed prediction and optimisation

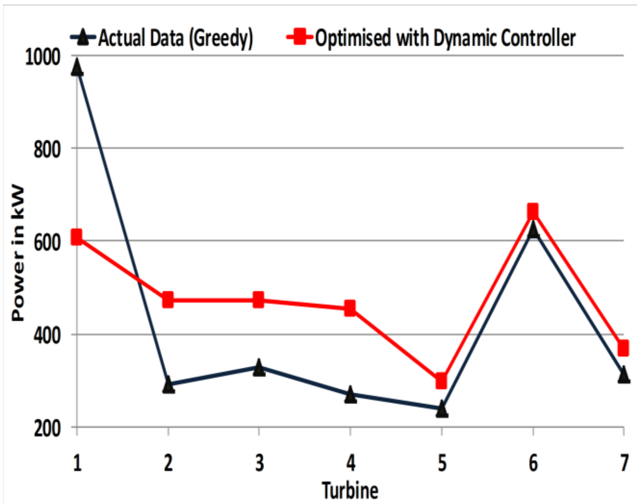

Fig 3: Power optimised with dynamic farm controller wind speed 8ms/ ± 0.5 and parallel to turbine array

Table 2: Results of optimisation

Variables	Brute Force	PSO	GA	SA
Population Size	NA	50	50	NA
Iterations	1.5625×10^{10}	20	51	250
Processing Time (Seconds)	8400	0.33	0.51	2
Calls to Wake Model	7.8×10^{11}	6654	85200	7854
Cp1	0.328	0.328	0.328	0.328
Cp2	0.345	0.345	0.345	0.345
Cp3	0.35	0.368	0.368	0.368
Cp4	0.396	0.398	0.398	0.398
Cp5	0.40	0.40	0.40	0.40
Cp6	0.40	0.40	0.40	0.40
Power in kW	3385	3335	3335	3335

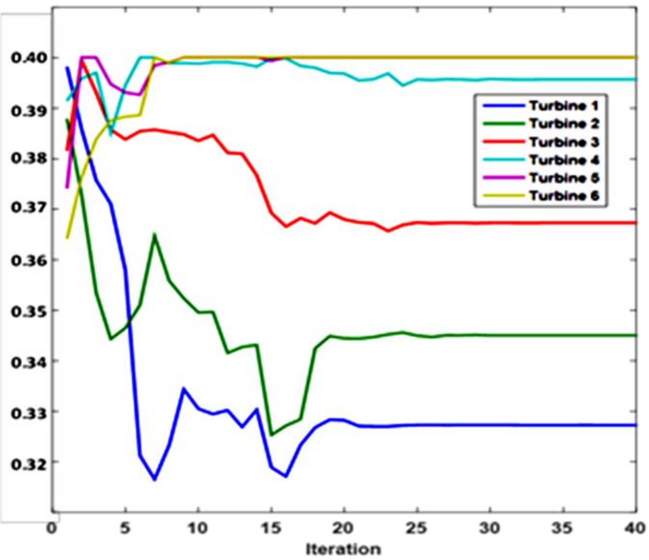

Fig 4: Movement of some random PSO particles towards Optimum Cps

VII. Conclusion

A dynamic wind farm controller is presented for maximising the farm output with coordinated control of turbines. A wind deficit model based on the Jensen model is developed. A correction factor is applied to the wake decay coefficient inside the wind farm. This model was used for producing different sets of turbines' outputs. Heuristic based optimisers were used for selecting set of outputs which can increase the combined production. It is concluded that PSO outperforms other optimisers. It has high computationally efficiency and uses minimum number of trials for reaching an optimum solution. The farm controller was tested with data from the Brazos wind farm. It is concluded that the farm controller can be used online as it completes the whole process within a few seconds. A power increase of up to 9% can be achieved in certain wind conditions High speed and accuracy makes the controller very suitable for practical industry use.

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