Energy and Wake effects Optimization of Offshore Wind Farm using PSO algorithm

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Abstract. As wind farms grow in size, the detrimental effects of wake interactions on energy yields become increasingly pronounced. This leads to the new challenge essential to the production of renewable energy. The two main objectives of offshore wind farm planning are to maximize annual energy production and minimize wake loss. To accomplish the twin goals of reducing wake impacts and maximizing energy production, this research tackles a novel method to investigate trade-offs between competing goals using multi-objective optimization algorithms. We introduce this problem with a sophisticated wake named the Bastankhah-Porté-Agel (BPA) model. To tackle this problem, the research has developed a multi-objective optimization framework in Python that shows the Pareto front, which illustrates the trade-off between wake effects and (AEP) by using a particle swarming optimization (PSO) algorithm. The proposed multi-objective optimization framework offers a disciplined way to balance energy production and wake loss, which advances the offshore wind farm design. The results indicate that the proposed method is robust in finding the optimized layout for improving sustainability and offshore wind energy efficiency. Before carrying out this process, the proposed tool has been validated using data obtained by *a wind farm* in Georgia.

1 Introduction

Offshore wind farms continue to grow in size, this causes operation, design, and sustainability to become more challenging. Economic profitability and environmental impact are two main aspects of the design [1]. The first one is defined by the annual flow of income minus expenses once of the investment and a provision. The second one is usually a major factor to determine aspect of the project's success during the planning and acceptance process. Wind variability poses a significant challenge in the deployment of wind farms, the unpredictable nature of wind patterns makes energy production planning difficult as Wind Turbine Interactions, Environmental Constraints, Maintenance, Reliability

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and Grid Integration. In the wake region, the power production of a wind turbine is lower than that of an upstream wind turbine due to the velocity deficit. Therefore, the best method to raise Annual Energy Production (AEP)of a wind farm is to reduce the overlap of the wind turbine swept areas and the wake regions as much as possible. For this purpose, optimization plays a critical role in many area, therefore, adapting wind farms to variable wind conditions. Optimization of a wind farm layout[2], [3], [4], [5], [6], [7], [8], [9], [10], [11], have been utilized to avoid wake regions. In the present study, a particle swarming optimization (PSO) algorithm is used for optimization of offshore wind considering simultaneous of Energy production and Wake effects , tackling this problem is challenging with both effect of the wind farm power production and its loss of power increases with the wake effect in order to find the best solutions. In the recent years, the specific area where to build the wind farm was assigned by governments. Existing wind farms present different shapes with diverse degrees of regularity [12,13]. Many academic optimization algorithms study discrete variables for independently locating each of the turbines [14]. In several institutions, such as in the New England Wind Energy Area, there is an imposition for uniform layouts to address navigation safety, the creation of distinct transit corridors, and the facilitation of vessels and aircraft[15]. Optimizations made restricting to uniformly distributed turbines show very small differences in the resulting energy yield, equal to or less than 1% [1, 16, 17]. The Horns Rev Offshore Wind Farm from Denmark, which was installed is an example of optimal sizing of offshore wind farms. It is a challenging issue in the wind turbine engineering design research and industry. In the last years, several researchers have been studying optimizing wind turbine design. In the literature, two different approaches are used. The first one uses parsimonious models based on international standards, whilst guaranteeing the required strength and stability [18] [19] [20]. The second one uses higher fidelity models to achieve interesting performances [21] [22] [23] [24] [25]. This work presents Multi-objective optimization of offshore wind farms considering two objective functions energy production and wake effects, which will be respectively maximized and minimized. This work uses an approach similar to build a decision support tool, for local small businesses, and evaluate the effect of wind turbines in large wind farms on the total energy loss of the wind farm. This paper is organized as follows: section 2 presents a brief presentation of Wake effect model and energy production; section 3 details Multi-objective optimization used in this work, while section 4 gives the results and their interpretations are discussed in this section. The conclusion of this proposed work is given in section 5.

2 Wake effect Model and energy production

2.1 Bastankhan-Porté-Agel (BPA) model

Wind turbines harness energy from the wind, leading to a reduction in energy content in the downstream wind compared to the upstream wind. The manifestation of this phenomenon is known as the wake effect, arising from the interaction between the wind and the turbine blades. In this interaction, the wind undergoes a deceleration, becoming slower and more turbulent, ultimately creating a wake behind the wind turbine. As the wind progresses downstream, the wake expands and gradually reverts to the surrounding wind characteristics. In the context of a wind farm with multiple turbines, the swept area of a turbine is often influenced by one or more upstream turbines, a phenomenon referred to as the shadowing effect.The slowed and turbulent nature of the wind in the wake signifies a diminished availability of energy. Additionally, turbulence introduces another detrimental factor by amplifying fatigue damage, there by compromising the reliability of the turbines [26]. Both of these consequences contribute to a reduction in the energy output of a Wind Turbine Generator (WTG), ultimately resulting in decreased energy production by the wind farm. Figures 1 shows an example of wake interactions and structure of wind turbines.

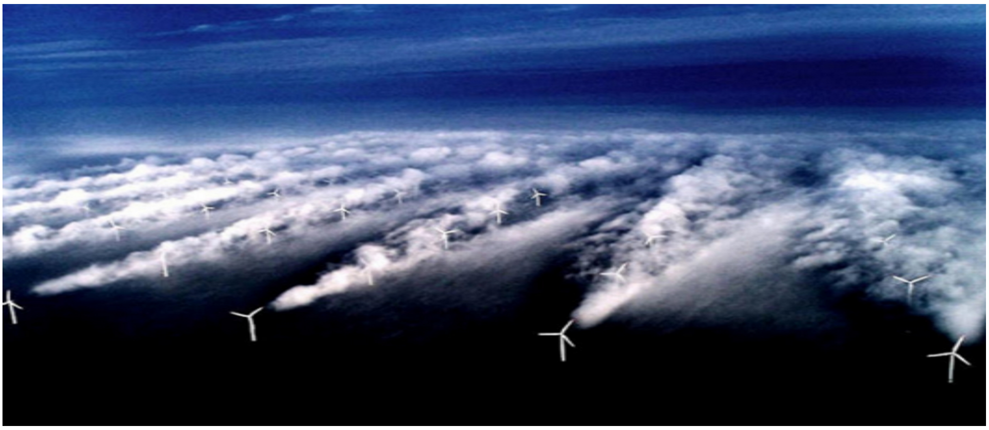

Fig. 1. Wake interactions in Horns Rev Offshore Wind Farm, Denmark[27]

Offshore wind farms generate wake losses. Therefore, it is critical to take into account these effects in all phases of our optimization framework. In the literature different wake model exist, in order to calculate the streamwise turbulence intensity in the wind-turbine ,based on the positive correlation between the added turbulence intensity and the thrust coefficient, Frandsen proposed an analytical model for the added streamwise turbulence intensity for the first time [28]. Furthermore, Crespo developed a new analytical model for the added turbulence intensity, the Jensen model [29]. Such models have the potential for a more precise wake estimation when accounting for atmospheric properties [30–31], and computational fluid dynamic simulations can be used to estimate the wake effects. In the placement of wind turbines within a predefined boundary, it is critical to consider the wake effects that generated by turbines, which is estimated to account for a 10 to 20% lower power production in large wind farms [32]. In this work (BPA) model has been employed to calculate energy production of wind farms. The motivation behind this proposed choice is that this model is a more advanced model, considering the impact of atmospheric stability and terrain effects against the Jensen model. In addition BPA model incorporates correction factors for different atmospheric stability conditions and provides a more accurate representation of wake dynamics. This wake model takes into accounts both near-wake and far-wake regions. To describe the evolution of the wake characteristics, the BPA wake model involves a set of mathematical equations that as a function of downstream distance.

The Mathematical formulation of this BPA wake model considers factors such as wind shear correction (Equation (1)), axial induction (Equation (2)), radial wakeexpansion (Equation (3)), velocity deficit (Equation) (4) and (5)) and turbulence intensity correction (Equation(6)).

- Wind shear correction

Wind shear is defined as the variations of wind speed over either horzonital or vertical distances. This
phenomenon is incorporated in BPA model, especially inatmospheric conditions. It is given by Equation (1).

$$U_y = U_r * \left(h/h_0\right)^{(1/3)} \tag{1}$$

h, h0 and Ur represents respectively hub height , reference height and radial component of the wind speed in the wake.

- Axial induction factor

Axial induction factor is the fractional decrease in wind velocity between the freestream and the turbine rotor. It is provided by Equation (2).

$$a = 2/\left(\left(1+\sqrt{\left(1-a_0 * \exp\left(-x/lam\right)\right)}\right)^2\right) \tag{2}$$

where ,
a0 is the axial induction factor, lam is the tip-speed ratio

- Radial wake expansion

In the context of wind energy, when a wind turbine operates, it creates a region of disturbed and slowed airflow downstream of the rotor, known as the radial wake expansion , that describes how this wake broadens as you move farther away from the turbine along the radial direction, which is perpendicular to the axis of the rotor. The Radial wake expansion is provided by Equation (3).

$$sigma_y = k * r + \sqrt{\left(\left(kappa * x * r\right)/2\right)} \tag{3}$$

where,
k and x are parameters

- Velocity deficit in the near-wake

Velocity deficit in the near-wake refers to the reduction in wind speed that occurs immediately downstream of a wind turbine rotor. As the turbine extracts energy from the wind. This phenomenon is a consequence of the aerodynamic interaction between the rotating blades and the wind. Understanding and modeling the velocity deficit in the near-wake is crucial for optimizing wind farm layouts and predicting the performance of downstream turbines. The formula for calculating the Velocity deficit in the near-wake expressed by equation as 4.

$$U_r = U_{inf} * \left(1-\sqrt{\left(1-Ct/\left(8 * sigma_y\right)\right)}\right) \tag{4}$$

where ,

Uinf is the undisturbed wind speed, Ct is the thrust coefficient of the turbine

- Velocity deficit in the far-wake

Velocity deficit in the far wake refers to the continued reduction in wind speed at greater distances downstream from a wind turbine. In this region, the wake continues to influence the wind speed, though the impact diminishes with increasing distance. Therefore, accurate characterization of the velocity deficit in the far wake is essential for understanding the overall wake behavior in wind farms and optimizing the spacing and arrangement of turbines to maximize energy extraction efficiency. the velocity deficit in the far wake is provided by Equation (5).

$$U_{fr}=2 * U_r/\left(\left(1+\sqrt{(1-a)}\right)^2\right) \tag{5}$$

- Turbulence intensity correction

$$U_{r-tidle}=U_y/\left(1+\left(U_y/U_{inf}\right) * \sqrt{(k/2)}\right) \tag{6}$$

where, k is the turbulence intensity at the rotor.

2.2 Annual energy production (AEP)

Nowday, to assess the performanec and economic viability of an offshore wind farm, the key metric is used the AEP, is also one of the important references for the investment decision, and accurate evaluation can reduce investment risks. The formula for calculating the annual energy production expressed by equation (7).

$$AEP=C.A.P.H.CF \tag{7}$$

where, C is the wind farm capacity, A is the total number of hours in a year, P is the efficiency or performance factor of the wind farm, H is the hub height wind speed , and CF is the capacity factor, representing the fraction of the wind's energy that is converted into electricity.

3 Multi-objective optimization

In the last decades, much research used a traditional approach, which converts the Multi-Objective (MO) problem into an Single-Objective (SO) problem by either aggregating the objective functions or treating the other as constraints. The SO problem can then be solved using traditional scalar-valued optimization techniques. Thesetechniques are geared towards finding a single solution and we have information about the objectives. Recently, several academic optimization algorithms used new approaches named Multi-objective optimization, the aim of this method is to obtain the Pareto front and then choose a variety of solutions. This article investigates how to balance energy production and wake mitigation, which advances in the offshore wind farm design. Among the most efficient evolutionary algorithms used of the for solving multi-objective constrained optimization is NSGA-II (Non-dominated Sorting Genetic Algorithm) [33]. It is a modified version of the NSGA algorithm [34], which is a fast and elitist MO genetic algorithm, in addtion a Strength Pareto Evolutionary Algorithm (SPEA) considerd an MOO algorithm.In other words, SPEA is closely related to other evolutionary algorithms such as the NSGA, Vector-Evaluated Genetic Algorithm (VEGA), and Pareto Archived Evolution Strategy (PAES). SPEA has two versions, more extensions can be found under the name SPEA+ and iSPEA. The aim of this algorithm is to locate and maintain a collection of non-dominated solutions (Pareto front) by examining thoroughly the search area by following an evolutionary procedure. In this work, all simulations were made using the optimization within (PSO) for solving the problematic. This PSO algorithm has a great efficiency and adaptability to various dynamic environments. It is the most successful optimization method currently available among nature-inspired algorithms, such as simulated annealing, genetic algorithms, differential evolution, fireflies, cuckoos, etc. PSO have been well-adopted in a number of research areas e.g. robotics, aerospace engineering and artificial intelligence. It should be noted that the benefits of PSO can be summed up in three ways: 1) there are comparatively few parameters that need to be adjusted; 2) the PSO algorithm has a quick convergence rate; and 3) the PSO algorithm is easy to implement. PSO has gained popularity as a strategy for solving optimization issues in recent years due to its ease of implementation and technical benefits.

3.1 Particle swarming algorithm: overview

The increasing complexity and high degree of certain optimization has led to the rise in popularity of the meta-heuristic algorithms methods for problem solving [35, 36, 37]. PSO algorithm was first proposed by Kennedy and Eberhart in 1995 [38]. PSO uses a population of potential solutions known as particles. Every particle in the search space has a position and a velocity associated with it, representing a potential solution to the optimization issue.
The particles "move" over the search area in an attempt to find the best answer to the given issue. A particle's velocity determines its direction of travel and is updated at each iteration, then the velocity changes the particle's position. The particles are arranged into

neighborhoods, which let the particles communicate with one another while they look for optimal conditions. Nearly from the invention of PSOs, the neighbourhood topology of the swarm has been the focus of research in the literature and is a significant component in PSO performance [39]. It has been demonstrated that various swarm topologies, or sociometries, such as star, ring, pyramid, and Von Neumann, affect PSO performance [40]. Figure 2 shows the various steps involved during the implementation of the PSO algorithm.

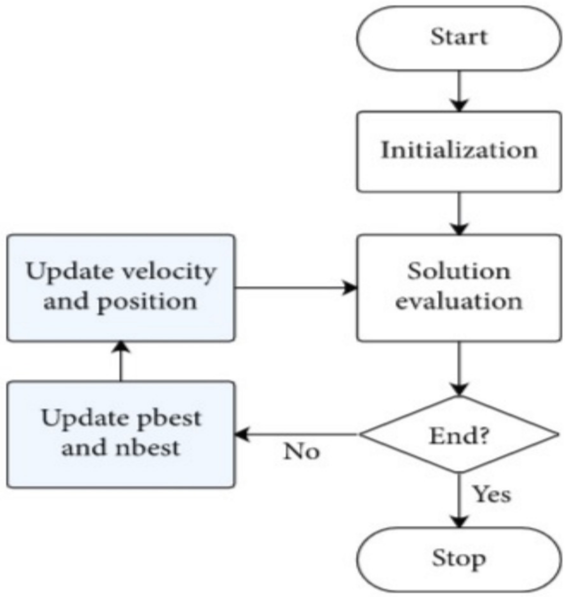

Fig.2. Implementation of the PSO algorithmm

Interestingly, a particle (also known as an individual)represents the possible optimization solution. Every person learns from the "movement experience" of both himself and others while they are searching.

3.2 Pareto Front

Through the definition of a function that checks dominance between two solutions, Pareto front is identified by analyzing dominance relationships among solutions, and a plot is generated to visualize the Pareto front in the objective space. Finally, the results of the PSO, including the optimal position and values, the Pareto front is displayed to illustrate the trade-offs between the two objectives functions.

3.3 Methodology

Our optimization framework is assigned places and velocities, which initiates the (PSO) method. The initial particle positions correspond to the initial personal best positions. Finding the particle with the highest AEP objective value yields the worldwide best position. Each particle's location and velocity are updated in the main PSO loop, which runs for a predetermined number of iterations, depending on its individual and global optimum positions. If the current AEP objective value is higher, the global and personal best positions are adjusted.

The algorithm returns the global best position, the AEP objective value at that location, and the outcome after completing the PSO cycle.

Table 1. PECIFICATIONS OF THE ANALYZED PARAMETERS

PARAMETERS	VALUE
Downstream distance	Tx = 100 (m)
Radial distance	r = 10 (m)
Undisturbed wind speed (m/s)	U_inf= 8 m/s
Thrust coefficient	Ct = 0.8
Radial wake expansion	sigma_y = 0.5
Capacity factor	CF = 1.0
Hub height	h = 80 (m)
Air density	rho = 1.225
Reference height (m)	h0 = 10 (m)
Axial induction factor at the rotor	a0 = 1 / 3
Tip-speed ratio	lam= 5
Hours in a year	C = 8760.0
Capacity factor Power coefficient	CF = 1.0 Cp = 0.45

Table 2. PECIFICATIONS OF THE ANALYZED PARAMETERS

num_particles	170
num_dimensions	2
max_iterations	2000

4 Results and discussion

To validate PSO, each algorithm was run with the parameters presented in Tables 1 and 2. The obtained results are also presented in the Figure 3, it can be seen that the multi-objective optimization of offshore wind farms considering both energy production and wake effects, with varying distributions of Velocity deficit in the near-wake and far-wake in addition we take into account the turbulence intensity correction.

The results indicate that the Pareto front, which is characterized by the Annual Energy Production (AEP) of offshore wind farms as one objective function and the Bastankhah-Porté-Agel model as another objective function, demonstrates a balance between maximizing AEP and minimizing wake effects.

As can be seen, almost evenly distributed optimal solutions are obtained. The Bastankhah-Porté-Agel model wake effects and the AEP of offshore wind farms gradually decrease, which is economically profitable. To reduce the cost. Therfore the PSO that was used shows robust power to solve multi-objective optimization problems.

The current study reveals that, optimal fitness front shows clearly, that the best compromise solutions are obtained between the two objectives functions while satisfying all the design constraints. In contrast to the results reported in Joongjin Shin's study on Wind Farm Layout Optimization Using a Metamodel and EA/PSO Algorithm in Gori Offshore shows in figure 4. Therefore this approach can be applied for new investigating of offshore wind farms during the preliminary design phase.

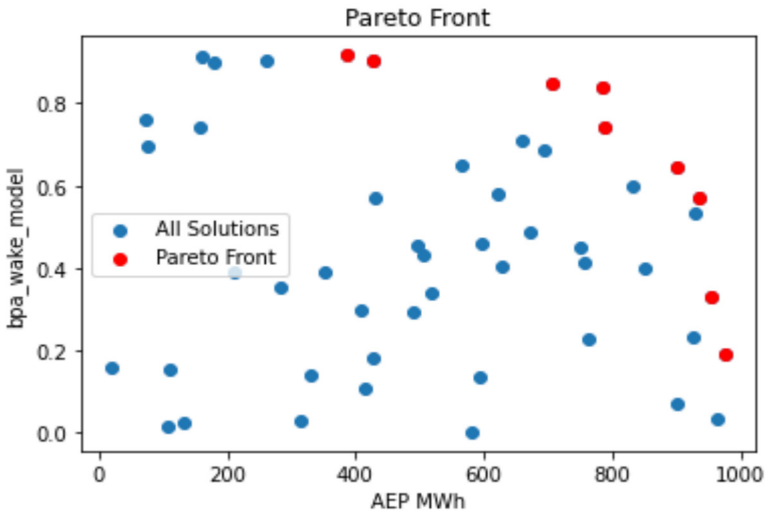

Fig.3. Pareto front

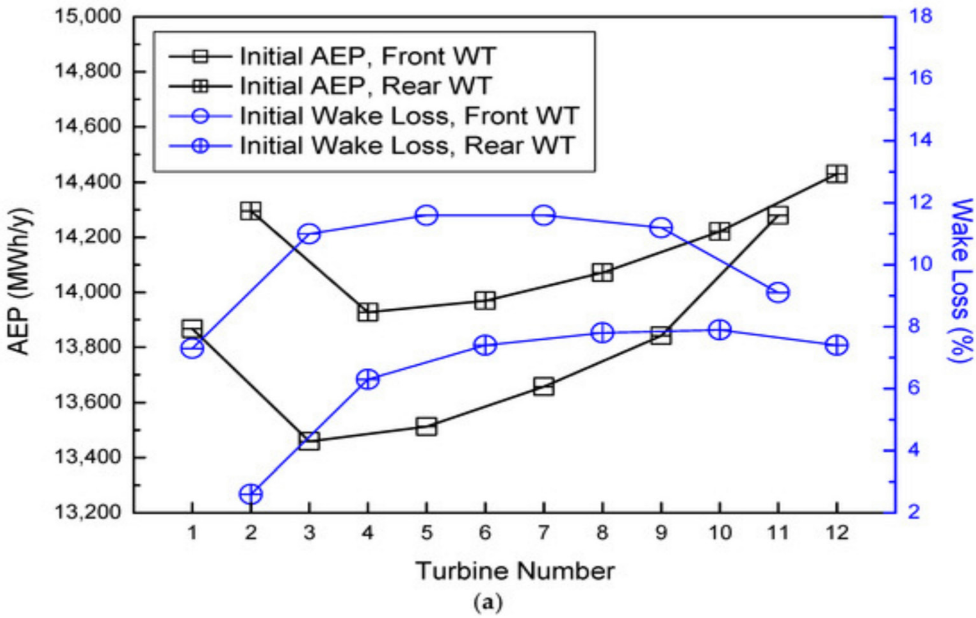

Fig.4. Optimal turbine layout for 12 WTGs at the Gori wind farm. best solution optimal solution[41]

5 Conclusion

The analysis of offshore wind farms wind becomes crucial and needs special attention, particularly in view of the wake effects. In the design of wind turbines, AEP is one of the most expensive in investment, this element has to be effective in its operation in terms of cost. In this research, the present findings confirm the power implementation of the PSO, for solving the multi- objective optimization approach. The main conclusion that can be drawn is that the PSO was shown to be successfully designed by minimizing the wake effects and maximizing AEP.

In future works, it will be interesting to take into account the constraints related to fatigue load and predict the maintenance cost of offshore wind farms.

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