Wind Farm Power Production and Fatigue Load Optimization Through Wake Steering

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Wind Farm Power Production and Fatigue Load Optimization Through Wake Steering

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***Abstract*— Wake steering has proven potential to increase wind farm production. However, this control strategy prioritizes the maximum power without considering the effects of fatigue load, a remaining life indicator on a wind turbine component. Reducing fatigue loads is one of the most important goals of wind farm control, especially for long-established wind farms. Therefore, it is crucial to consider the fatigue load when optimizing the yaw angles. This paper proposes a multi-objective wake steering control strategy to balance power production and fatigue load. Firstly, a power production model based on Gauss–Curl Hybrid (GCH) wake model is introduced to estimate the farm power. Secondly, a fatigue load prediction model is proposed based on Gaussian Process Regression (GPR). Finally, the Particle Swarm Optimization (PSO) method is adopted to optimize the yaw offset by considering the trade-off between power production and fatigue load. The proposed balancing strategy shows an increase in power generation by 16% compared to the baseline strategy (Greedy strategy) while reducing the average and maximum fatigue load by 12% and 10%, respectively.**

I. INTRODUCTION

Renewable energy has been increasingly adopted worldwide to replace traditional thermal power generation methods, which benefits in mitigating climate change. In 2021, wind power contributed an estimated 7% of total electricity generation [1]. However, it is essential to highlight that as the installation capacity of wind power increases, the distance between wind turbines decreases. This tight layout may affect structural loads and power losses because of the wake effect. For example, a significant power loss of about 23% has been observed at the Lillgrund offshore wind farm compared to the free stream [2].

Wind farm control has been proposed by the research community to maximize power production. Axial induction control (AIC) [3] and wake steering control (WSC) are well known. AIC, also known as pitch-based control, increases the output of downstream turbines by de-rating upstream turbines. It reduces the power coefficients (CP curve) by adjusting the pitch angle and generator torque but provides a low improvement in energy production [4]. On the other hand, WSC, also known as yaw-based control, improves the power generation of downstream turbines by changing the wake propagation direction of upstream turbines [5]. WSC has shown a potential to improve overall power production in large-edge simulation (LES) [6], wind tunnel experiments [7], and field tests [8]. These methods are usually compared with the baseline case without optimal control operations. Ryan et al. show a 15% improvement in the downstream turbine between two in-line turbines [9]. Howland et al. demonstrated an increase in power production by 21% using an array of three wind turbines in a wind tunnel [10]. Fleming et al. performed field tests to show an increase in energy extraction of up to 4% for an array of three turbines [11]. Sun et al. discuss the influence of wind speed and turbulence intensity on fatigue load [12]. Additionally, it was observed that yaw misalignment is more influential than wakes in case of fatigue load. The effect of yaw misalignment over the blade root fatigue load has been discussed in [13].

Recently some researchers have considered fatigue load in the wake steering strategy. A multi-objective optimization algorithm has been proposed to balance power generation (calculated by the Gaussian steady-state wake model) and fatigue load (computed by the blade-element-momentum model) [14]. This optimization algorithm reduces the load at the cost of a slight loss in power production. However, the optimization process is time-consuming due to blade-element-momentum calculations at each iteration step. Schmidt et al. used the single turbine load database (Modelica Library for Wind Turbines) to indirectly compute each turbine's fatigue load [15]. This computing method is simple and fast. However, the secondary effects of wake steering and wind farm blocking effect have not been considered.

In conclusion, although the wake yaw control improves the overall power generation, the load effect caused by the wake deflection is rarely considered. Some studies tried to balance power generation and fatigue loading. However, balancing the accuracy and computational costs in fatigue load estimation is challenging. For example, in Van et al. [14], the author observed high accuracy in fatigue load calculation but with a very high computational cost. Another fast but not sufficiently accurate fatigue load calculation has been discussed in [15].

This paper proposes a multi-objective wake steering control strategy to balance the goal of improving power production and minimizing fatigue loads. Specifically, A machine learning method is proposed to predict the farm fatigue load, and the multi-objective optimization capability of particle swarm optimization (PSO) is used to find the optimal yaw control strategy. This article contains the following novel contributions:

(1) A multi-objective yaw control strategy to balance wind farm power production and fatigue damage; (2) A Gaussian Process Regression (GPR) model to estimate the fatigue damage.

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The paper is organized as follows: Section II describes the power production model and the fatigue load calculation method. The main framework is illustrated, and the optimization problem is explained in Section III. Lastly, case study results and conclusions are presented in Sections IV and V, respectively.

II. Wind Power and Damage Modeling

A. Power Production Model

The static wake model is generally used for the estimation of power production. Among them, the engineering wake model Floris is popular because of its accuracy and computational cost [16]. Specifically, the Gauss-Curl Hybrid (GCH) model was implemented in Floris, which combines the Gaussian wake model [17] and curled wake feature [18]. Accordingly, two modifications were introduced to improve the accuracy and computational cost. One is utilizing yaw-added recovery to simulate the effect of the yaw-induced vortices. Another is using secondary steering to model the impact of vortices. The GCH power production model can be described as the following equation:

$$P = \frac{1}{2}\rho A C_p U^3 \cos(\theta)^{p_p} \tag{1}$$

where, P is the power, ρ is the air density, A is the area of the rotor, U is wind speed, θ is the yaw offset, and C_p is the power coefficient, p_p is the deflection parameter to match the maximum power coefficient and generator efficiency ($p_p = 1.88$ for NREL-5MW turbine in [4]).

B. Damage Equivalent Loads (DELs)

Damage Equivalent Load (DEL) is an important metric for evaluating the failure lifetime of a component. The calculation of DEL involves a series of post-processing steps starting from raw load data. Two commonly used methods for post-processing are the Rain flow counting (RFC)and the Palmgren-miner (PM) rule. The RFC method uses simple stress combinations to equate complex stress spectra [19]. Subsequently, the PM rule computes the RFC results to equivalent damage loads by considering the linear damage curve [20].

For a raw load signal in the form of a time series, the RFC can extract a list of stresses amplitude s_i and corresponding cycles n_i. A damage factor is defined here to measure the effects of cycles against the total number of failure cycles (N_i) at a given stress amplitude.

$$d_i = \frac{n_i}{N_i} \tag{2}$$

According to PM rules theory, the relationship between different stress amplitudes and their corresponding failure cycles is linear in the log-log coordinate system. The slope ratio in a linear relationship is $1/m$ (m is the Wohler exponent).

$$N_i = \left(\frac{S_0}{S_i}\right)^m \tag{3}$$

The damage factor (2) can be rephrased as follows::

$$d_i = \frac{n_i}{N_i} = \frac{n_i S_i^m}{S_0^m} \tag{4}$$

The total damage of a signal is equal to the sum of each stress damage, and L is the number of stress amplitudes from a signal:

$$DEL = \frac{1}{S_0^m}\sum_{i=1}^{L} n_i S_i^m \tag{5}$$

Assume that all stress amplitudes and cycles are equivalent to a fixed stress amplitude S_{eq} and cycle n_{eq}. The total damage can be rewritten as follows:

$$\frac{n_{eq}S_{eq}^m}{S_0^m} = DEL = \frac{1}{S_0^m}\sum_{i=1}^{L} n_i S_i^m \tag{6}$$

Finally, by transferring the signal to 1 Hz sinusoidal stress, the total damage can be described by the same length signal with different amplitudes.

$$S_{eq} = \left(\frac{n_i S_i^m}{n_{eq}}\right)^{\frac{1}{m}} \tag{7}$$

III. Yaw offset optimization

In this section of the paper, the proposed optimization framework is described. Specifically, a machine learning model is introduced to predict the fatigue load. Then, the optimization problem was presented, including the objectives and constraints.

A. Optimization Framework

Wake affects both the power production and fatigue load. When both power production and fatigue load are considered, the wake steering control is a multi-objective optimization problem. Fig. 1 shows the flow chart of the proposed multi-objective optimization algorithm. From the start, a series of wind files are generated according to the FAST.FARM simulation, and then the raw load data of the wind turbine components are obtained. This raw load data is processed through the fatigue module to obtain the fatigue load. The fatigue load is then trained with the corresponding input parameters to the GPR model. The trained GPR model is used to predict the fatigue load. Finally, PSO is introduced to optimize the yaw angles.

B. GPR Model Prediction Procedure

Gaussian process regression (GPR) is a mature machine-learning method for regression tasks. It is a non-parametric and kernel-based Bayesian approach. Therefore, GPR has several benefits, such as high performance on smaller datasets and the ability to provide uncertainty measurements on the predictions [21]. Furthermore, it fits complex problems with nonlinearity and high dimensionality.

The Gaussian process regression $f(x)$ can be formulated by the following equation with the training x and testing data x'):

$$f(x) \sim GP(m(x), k(x, x')) \tag{8}$$

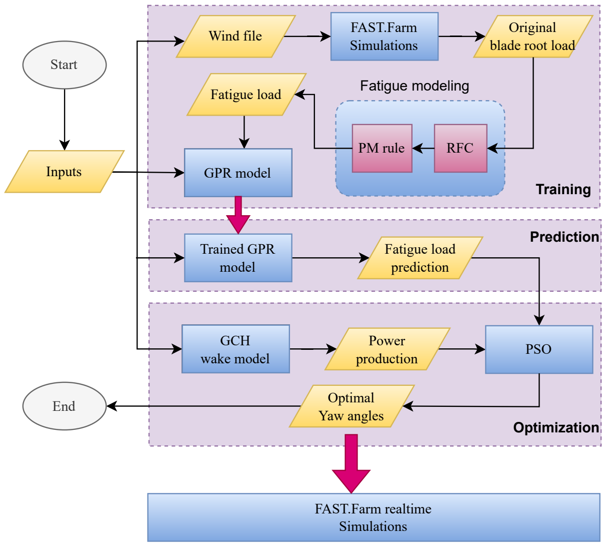

Fig. 1. Flow chart of proposed multi-objective wake steering control strategy.

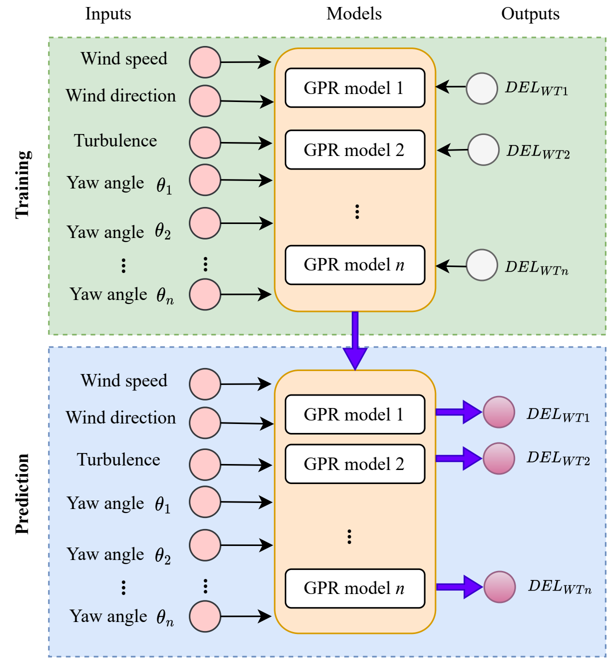

Fig. 2. GPR prediction procedure.

where $m(x)$ is the mean function.

$$m(x) = E[f(x)] \tag{9}$$

and $k(x, x')$ is the covariance function of the data

$$k(x, x') = E[(f(x) - m(x))(f(x') - m(x'))] \tag{10}$$

Fig. 2 illustrates the GPR prediction process, which comprises two main phases: training and prediction. During the training phase, the GPR models are trained using inputs (wind speed, wind direction, turbulence intensity (TI), and yaw angles) and corresponding outputs (damage equivalent loads). After a long training period, the trained models can be used for prediction by providing the inputs. For a wind farm containing n turbines, n GPR models are required to handle the load prediction.

C. Optimization Problem

The key to the multi-objective optimization problem is defining the optimization objective. However, before describing the optimization objective, the following two equations are used to measure the power production and fatigue load in the optimal strategy:

$$P(\theta_i) = \frac{P_{opt}(\theta_i)}{P_{baseline}(\theta_i)} \times 100\% \tag{11}$$

where, $P(\theta_i)$ is the normalized power of turbine i under optimal strategy compared with the baseline strategy, the $P_{opt}(\theta_i)$ is the power production of turbine i under the optimal strategy, $P_{baseline}(\theta_i)$ is the power production of turbine i under the baseline strategy.

$$D(\theta_i) = \frac{D_{opt}(\theta_i)}{D_{baseline}(\theta_i)} \times 100\% \tag{12}$$

where, $D(\theta_i)$ is the normalized fatigue load of turbine i under optimal strategy compared with the baseline strategy, the $D_{opt}(\theta_i)$ is the fatigue load of turbine i under the optimal strategy, $D_{baseline}(\theta_i)$ is the fatigue load of turbine i under the baseline strategy.

The final optimization objective is defined by:

$$\begin{aligned}\min_{\theta} \quad \Theta(\theta) = -(&\alpha_1 \times \|P(\theta)\|_1 \\ &- \frac{\alpha_2 \times \|D(\theta)\|_1}{n} - \alpha_3 \times \|D(\theta)\|_\infty)\end{aligned} \tag{13}$$

where, $\Theta(\theta)$ is the final cost function that needs to be minimized, $\|.\|_1$ and $\|.\|_\infty$ are the first and infinity norms, $\|P(\theta)\|_1$ is sum of the power, $\|D(\theta)\|_1$ is the sum of fatigue load, $\|D(\theta)\|_\infty$ is the max value of fatigue load, and α ([α_1, α_2, α_3]) is a weighting vector.

The constraint on the yaw angles is:

$$\textbf{s.t.} \mid \theta_i \mid \leq 30^\circ \tag{14}$$

D. Yaw Offset Optimization Procedure

Particle swarm optimization is a multi-objective optimization algorithm that selects the best solution from a set of candidate solutions by iteration [22]. The optimization procedure is shown in Fig. 3. At the beginning of optimization, the particle swarm's position and optimal position are initialized. The position is the optimized variable (the yaw angles in this paper). Then the power production and fatigue load can then be extracted from the GCH and Fatigue load models. Then If the fitness function meets the optimization criteria, the optimization procedure is completed. Otherwise, the updating in position and update direction will be executed, and the upper steps will continue until the optimization criteria are met. Generally, the optimization criteria include the number of iterations and iteration errors.

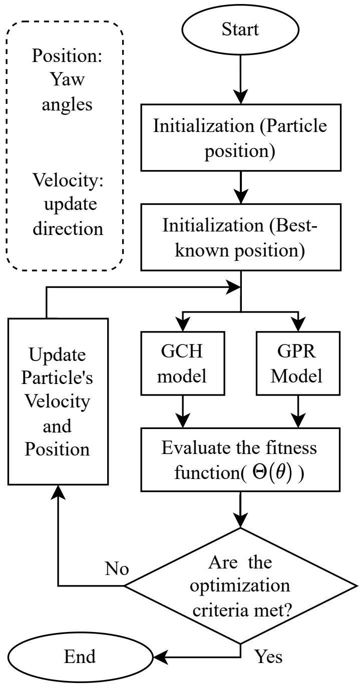

Fig. 3. PSO optimization procedure.

IV. Results

The wind farm in this paper comprises three wind turbines arranged in a row and separated by five times the rotor diameter. The model of the fan is NREL-5MW. The wind inflow condition is 9m/s in wind speed and 5% in turbulence intensity.

A. Case Study

Table I shows three farm control strategies: Baseline, Maximum power (MaxPower), and Damage considered (DamageConsidered) strategy. Among them, the Baseline strategy is the baseline case without yaw misalignment. The MaxPower strategy is the optimal yaw offset to achieve maximum power. Finally, the DamageConsidered strategy is optimal yaw offset to balance the power production and fatigue damage.

TABLE I
Control strategies

Control Strategy	Objective	Yaw angles
Baseline	-	No yaw, keeps zero
MaxPower strategy	Maximum power	Optimal yaw angles
DamageConsidered strategy	Balancing power and fatigue	Optimal yaw angles

B. Power Production Results

The Floris simulations for the Baseline and the MaxPower strategy are shown in Fig. 4 and Fig. 5. The Baseline strategy is set to a yaw offsets [0,0,0] degree with a power production of 1 (Normalized). The MaxPower strategy shows an optimal yaw offset [30,27.67,-2.87] with a power production of 1.24.

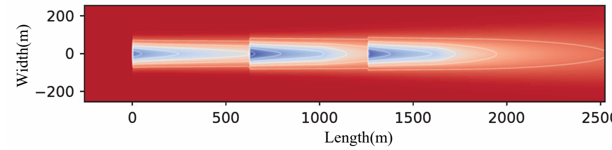

Fig. 4. The Floris results for the Baseline strategy with a yaw offset of [0,0,0]. Power production is normalized to 1 (Normalized value).

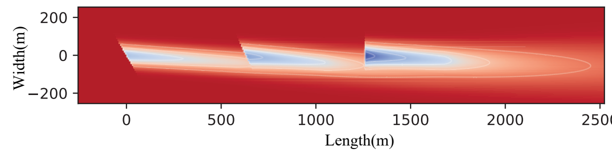

Fig. 5. The Floris results for the Maxpower strategy with a yaw offset of [30,27.67,-2.87]. Power production is 1.24 (Normalized value).

C. Fatigue load prediction Results

The accuracy of GPR prediction outperforms that of the TUT method, as demonstrated in [13]. For instance, under the specific wind conditions of a wind speed of 9m/s and turbulence intensity of 5%, the GPR reveals a lower prediction error (RMSE) of 15.19%, compared to the Lookup Table (LUT) method's error of 50.09%.

D. Yaw Offset Optimization Results

The optimization results can vary based on the weights assigned to different factors. In this section, two weight combinations will be mentioned for comparison purposes. The first weight combination is [1, 0, 0], which makes the DamageConsidered strategy similar to the MaxPower strategy, focusing on maximizing power generation. The second weight combination is [0.33, 0.33, 0.33], applying equally important to power generation, average fatigue load, and maximum fatigue load in the PSO algorithm.

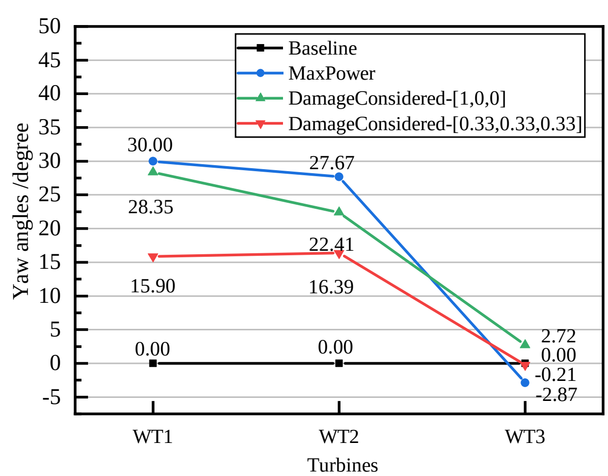

Fig. 6. Optimized yaw angles.

Fig. 6 shows the optimal yaw angles under different strategies. With the weight of [1,0,0], the DamageConsidered is similar to the MaxPower strategies in optimal yaw angles. Specifically, The first turbine has the largest yaw deflection, followed by the second turbine, which has slightly less yaw deflection than the first turbine, and the third turbine, which has the minor yaw deflection. However, the DamageConsidered strategy with the weight of [0.33,0.33,0.33] differs from the MaxPower strategy. The optimal yaw angles are 15 and 16 degrees yaw angles at the first and second turbines, which is smaller than the MaxPower strategies.

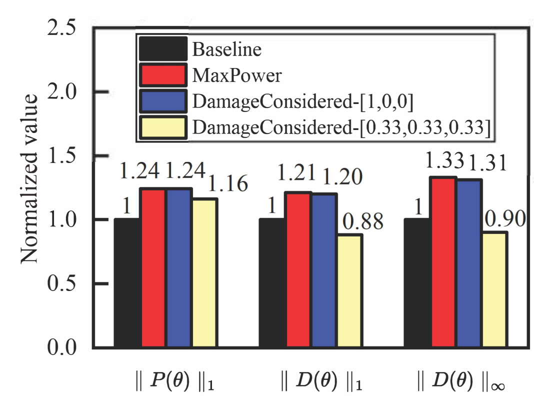

Fig. 7. Optimized power production and fatigue load.

Fig. 7 shows the power production and fatigue loads for different strategies, where the power and fatigue indicators in the Baseline strategy are normalized to 1. With the weight of [1,0,0], both the DamageConsidered and MaxPower strategy increases the 24% power production compared to the Baseline strategy. However, The MaxPower strategy has a 21% increase at average fatigue loads and a 33% increase at maximum fatigue loads, which is contrary to the target of fatigue load in wind farm control.

A slight increase in power production is sacrificed to decrease fatigue load. Compared to the Baseline strategy, the DamageConsidered strategy with the weight of [0.33, 0.33, 0.33] increases the power generation by 16% and reduces the average fatigue load by 12% and the maximum fatigue load by 10%. In this scenario, the DamageConsidered strategy differs from the MaxPower strategy because the fatigue load of the MaxPower strategy is higher than the baseline strategy. Specifically, The DamageConsidered strategy lost 8% of the power generation increase, but in exchange for a 33% reduction in average fatigue load and 43% reduction in maximum fatigue load compared with the MaxPower strategy.

V. CONCLUSIONS

This study proposed a balanced multi-objective wake steering control strategy considering power production and fatigue loads. The fatigue load model based on machine learning is proposed for fatigue prediction. Combining the power production model, a multi-objective optimization based on PSO can effectively balance the requirement for power gain and fatigue load reduction. The introduction of weights allows the proposed algorithm to flexibly adjust the importance of power production and fatigue load. The case study shows that a fixed equal weighting on all optimization objectives resulted in a 16% increase in power gain and a 12% and 10% decrease in average and maximum fatigue loads compared to the baseline strategy.

This paper does not consider the uncertainty of wake steering, but the uncertainty exists. This uncertainty leads to an inaccuracy in power and fatigue load estimation, affecting wake steering control's benefits. Various uncertainties in wake steering control will be considered in the future, especially yaw misalignment uncertainty.

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