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Optimal selection of time windows for preventive maintenance of offshore wind farms subject to wake losses

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Abstract

The maintenance of wind farms is one of the major factors affecting their profitability. During preventive maintenance, the shutdown of wind turbines causes downtime energy losses. The selection of when and which turbines to maintain can significantly impact the overall downtime energy loss. This paper leverages a wind farm power generation model to calculate downtime energy losses during preventive maintenance for an offshore wind farm. Wake effects are considered to accurately evaluate power output under specific wind conditions. In addition to wind speed and direction, the influence of wake effects is an important factor in selecting time windows for maintenance. To minimize the overall downtime energy loss of an offshore wind farm caused by preventive maintenance, a mixed-integer nonlinear optimization problem is formulated and solved by the genetic algorithm, which can select the optimal maintenance time windows of each turbine. Weather conditions are imposed as constraints to ensure the safety of maintenance personnel and transportation. Using the climatic data of Cape Cod, Massachusetts, the schedule of preventive maintenance is optimized for a simulated utility-scale offshore wind farm. The optimized schedule not only reduces the annual downtime energy loss by selecting the maintenance dates when wind speed is low but also decreases the overall influence of wake effects within the farm. The portion of downtime energy loss reduced due to consideration of wake effects each year is up to approximately 0.2% of the annual wind farm energy generation across the case studies—with other stated opportunities for further profitability improvements.

KEYWORDS
offshore wind farm, optimization, preventive maintenance, scheduling, wake effects

1 | INTRODUCTION

The U.S. Department of Energy's Wind Vision report expects that wind power should supply up to 20% of all U.S. electricity demand by 2030 and up to 35% by 2050, which includes 2% of the nation's total electricity generation in 2030 and 7% in 2050 from offshore wind power.[1] By 2050, in the coastal and Great Lakes states, which consume almost 80% of U.S. electricity, offshore wind farms are expected to contribute approximately 14% of the projected new electricity generation.[2] Compared with winds over land, offshore winds have larger strength and greater uniformity. Therefore, offshore wind farms can provide a higher and smoother rate of electricity generation than those land-based. The coastlines and lakeshores of the United States are capable of providing extensive and accessible offshore wind energy resources. By 2020, the Block Island wind farm and the Coastal Virginia wind farm were the two operating offshore wind projects in the United States. In March 2021, the Biden administration announced a set of actions that will accelerate the development of offshore wind energy. The Vineyard Wind project, the first commercial scale offshore wind farm in the United States, was approved by the federal government in May 2021, which is a significant leap in harnessing powerful offshore winds and reducing carbon emissions.

In order to keep wind turbines in consistent working conditions with reliable power output, regular and responsive maintenance is normally needed. Operation and maintenance (O&M) costs are significant components of the overall economy of wind projects, especially for offshore wind farms. For the same installed capacity, offshore O&M costs generally reach two to three times higher than those of onshore, primarily due to accessibility issues. For some European offshore wind farms, O&M costs vary from 18% to 23% of the total cost of a wind project.[3] It was estimated by the researchers from the U.S. National Renewable Energy Laboratory that O&M account for 34.3% of the total levelized cost of energy for fixed-bottom offshore wind turbines.[4] Therefore, careful and well-considered maintenance strategies are critical to the profitability and success of offshore wind projects.

1.1 | Operation and maintenance of offshore wind farms

A variety of decision support models have shown that O&M have a great influence on the economy of wind projects. Novel maintenance strategies have been constantly proposed to increase the reliability of turbines and reduce cost.[5–7] Opportunistic maintenance is one of the emerging concepts, which groups different types of maintenance activities of multiple turbines together to reduce costs.[8–12] Life cycle cost is an important measure used to assess the efficiency of turbine maintenance strategies.[13] To reduce this cost, prognostic health management is widely incorporated to determine turbine conditions and plan timely maintenance.[14,15] Aging models and degradation models of turbine components are also used to establish thresholds for starting maintenance activities, such as repairs and replacement.[16–18] Other key issues affecting the efficiency of wind farms, including the effects of wind velocity,[19] component-level repairs,[20] turbine system failures,[21] and personnel availability,[22] have been investigated by researchers as well.

Accessibility and logistics are important factors in the selection of maintenance strategies for offshore wind farms. Since vessels are the most common mode to carry maintenance personnel and wind turbine parts to offshore sites, the routing and scheduling of a vessel fleet have been studied by several research groups. The determination of optimal fleet size and mix of vessels,[23,24] the timing of jack-up vessel campaigns,[25] the optimal use of a maintenance fleet in terms of vessel capabilities and fleet size,[26] the optimal scheduling of crew transfer vessels using network planning method,[27] and the optimal scheduling of multiple crew transfer vessels from multiple bases to multiple sites[28] have been performed in the context of offshore wind farms.

The reduction in power caused by turbine shutdown for maintenance has been investigated with respect to time schedules, vessel routes, technician assignments, and turbine failures.[29–31] The purpose of this study is to investigate how to reduce energy loss of offshore wind farms subject to wake effects during preventive maintenance. Wake effects have been seriously considered in location selection for wind farms,[32] wind farm layout optimization,[33] reduction of fatigue loads on wind turbines,[34] and estimation of available power during curtailment.[35] The optimization of maintenance schedule has taken wake effects into account initially by Zhang et al.[36] The coupling between maintenance and wake effects was investigated using randomly generated stochastic sampling wind speed and direction by Ge et al[37] and Yin et al.[38] However, the reduction in power generation caused by wake effects during maintenance has not been thoroughly studied in practice. To bridge this gap, the current study investigates how an optimized maintenance schedule reduces downtime energy loss due to wake effects using real climatic data. In this deterministic approach, the energy saving due to consideration of wake effects in maintenance planning can be accurately evaluated.

1.2 | Preventive maintenance

Wind turbine maintenance includes three major categories of actions:

1. **Preventive Maintenance:** Regularly performed to support a turbine in satisfactory operating condition, which reduces the probability of failures.
2. **Predictive Maintenance:** Performed when some indicators show that a turbine tends to fail.
3. **Reactive Maintenance:** Performed after a turbine experiences problems or has stopped working.

Preventive maintenance activities include systematic inspection, detection, and correction of incipient failures, which are essential to keep efficient operation of wind turbines. Preventive maintenance is normally carried out twice a year, and each maintenance event requires 2 to 3 days of downtime per turbine.[39] To reduce the power fluctuation of a wind farm, only a limited number of turbines in a wind farm are generally maintained at the same time. The downtime energy losses caused by the shutdown of turbines are principally determined by wind conditions. It is desirable to perform preventive maintenance when shutdown will result in the least reduction in energy generation. For offshore wind farms, accessibility is a critical factor influencing their maintenance schedules. Site weather conditions, including wind speed, wave height, and skin temperature, should satisfy the safety standards for maintenance personnel.[40] To safely transport maintenance personnel and turbine parts, the operation of vessels also requires weather conditions to meet specific standards.

The three types of maintenance are not fully independent from each other. This paper focuses on the schedule optimization of preventive maintenance alone. During the scheduled time windows for preventive maintenance, predictive or reactive maintenance might also need to be performed. Combined scheduling of these three types of maintenance together will provide more opportunities to reduce expenses and consequently improve the profitability of wind farms.

1.3 | Wake models

Wind turbine wakes are caused by the momentum deficit and increased level of turbulence created by turbines in a wind farm, which can result in a reduction in power generation and unsteady loads on other turbines.[41] Caused by wake effects, the power supply of a wind farm is considerably less than the simple product of the power extracted by a stand-alone turbine and the number of identical turbines in the farm.[42] Since wake recovers at some distance downstream, power deficiency of turbines in wakes generally declines as turbine spacing increases.[43,44] However, the distances between turbines in a wind farm cannot be sufficiently large for complete wake recovery. Several methods can be used to reduce overall wake effects,[45–47] which have to be taken into account to accurately evaluate the total power generation of a wind farm.

Many studies have been dedicated to the development of wake models with different levels of fidelity and computational efficiency. These models can be generally classified into three categories[48]: (i) low-fidelity engineering wake models based on fundamental fluids principles, (ii) medium-fidelity wake models using modified RANS (Reynolds-averaged Navier-Stokes) or variations of the actuator disk model, and (iii) high-fidelity CFD (computational fluid dynamics) wake models.

Engineering wake models demand low computational cost to simulate macroscopic average effects of wakes. Based on the assumption of self-similar velocity deficit profiles, the Park wake model was proposed to derive downstream wake velocity.[49] The Larsen wake model uses first- and second-order approximations of the RANS equations.[50] The Frandsen wake model modifies the wind velocity profile to consider downstream distance.[51] Bastankhah and Porté-Agel proposed a single-Gaussian distribution to approximate the wake velocity in far wake,[52] and it was later improved using a double-Gaussian distribution.[53,54]

The medium-fidelity dynamic wake meandering model[55] and Fuga wake model[56] numerically solve simplified RANS equations to evaluate wake deficit, turbulence, and meandering. Another branch of medium-fidelity wake models includes some variations of the actuator disk model.[57,58]

High-fidelity CFD wake models consider computationally expensive approaches,[59] such as the RANS equations, large-eddy simulations, or direct numerical simulation. Two major developers of CFD software in the area of wind farm modeling are EllipSys3D[60] and OpenFOAM.[61,62]

The high-fidelity CFD wake models simulate small scales at extremely high computational cost. Therefore, they are often used as a reference for tuning and validating low-fidelity wake models.[63,64] Engineering wake models are particularly suitable for optimization problems, which involve a large number of iterations, such as wind farm layout planning[65,66] and control-oriented wake steering.[67] To facilitate optimization, machine learning and surrogate modeling can be used to develop fast data-based wake models with reasonably high accuracy.[68–70] Before reaching an optimal solution for the schedule optimization problem formulated in Section 3 using the genetic algorithm, approximately 10,000 evaluations of a wake model are required. Therefore, a low-cost engineering wake model is employed to evaluate the power generation of an offshore wind farm in this study.

The remainder of this paper is organized as follows. Section 2 describes the power generation model used to evaluate the energy production of a wind farm, which takes wake effects into account. Section 3 formulates a schedule optimization problem to select optimal time windows for turbine maintenance. Section 4 presents a case study of maintenance schedule optimization for a utility-scale offshore wind farm. Concluding remarks are presented in Section 5.

2 | WIND FARM POWER GENERATION

2.1 | Wake effects

The impact of four analytical wake models, the Jensen model,[49] the Larsen model,[50] the Frandsen Model,[51] and the Ishihara Model,[71] on the estimation of wind farm power output was investigated by Tong et al.[72] Any of the models can provide satisfactory estimation of energy generation considering wake effects. This study uses the Frandsen wake model, which employs the control volume concept to relate thrust and power coefficients to velocity deficit.

At a distance s downstream behind a turbine with a diameter D, the diameter D_{wake} of the wake front is expressed as

$$D_{wake} = (1+2\alpha\bar{s})D, \\ \text{where} \quad \bar{s} = s/D. \tag{1}$$

The parameter α is the wake spreading constant, which is determined by the formula

$$\alpha = \frac{0.5}{\ln\left(\frac{z_H}{z_0}\right)}, \tag{2}$$

where z_H and z_0 are the average hub height of turbines and the average surface roughness of wind farm region, respectively.

If the wind approaches a turbine at velocity U, the velocity U_{wake} in the wake is expressed as[73]

$$U_{wake} = \left(1 - \frac{2a}{(1+2\alpha s)^2}\right)U. \tag{3}$$

where a is the induction factor, which can be determined from the coefficient of thrust. The coefficient of thrust is one of the design characteristics of a turbine rotor.

2.2 | Wind farm power generation model

In this paper, a wind farm power generation model adopted from earlier work in wind farm layout optimization is used.[74–76] This model evaluates the power generated by a given number of wind turbines with specified locations in a wind farm subject to a given wind condition. It is suitable for the evaluation of wind farm power generation under various maintenance schedules. This power generation model uses the Frandsen wake model described in Section 2.1 to calculate the power output of the entire wind farm influenced by wake effects. Site wind speed and direction are inputs to the model to calculate power generation.

The total power P_{all} generated by N turbines is the sum of the power generated by individual turbines, which can be expressed as

$$P_{all} = \sum_{i=1}^{N} P_i. \tag{4}$$

To evaluate downtime energy loss of a wind farm during preventive maintenance, the energy generated by the farm when all turbines are operating and that when the turbines not being maintained are operating should be calculated under the wind conditions in the maintenance time interval. The difference between these two energy outputs is the downtime energy loss. When a set, S, of M turbines are shut down for maintenance, these M turbines are not taken into account in the power generation model; only the power generated by the operating turbines is summed up. The wake effects of the non-operating turbines (under maintenance) are not considered. The power generated by all operating turbines (without the M turbines) is

$$P_{operating} = \sum_{\forall i \notin S} P_i. \tag{5}$$

The power loss is given by

$$P_{loss} = P_{all} - P_{operating}. \tag{6}$$

During a maintenance time window from t_{start} to t_{end}, the energy loss can be expressed as

$$E_{loss} = \int_{t_{start}}^{t_{end}} P_{loss}(t)\,dt. \tag{7}$$

In order to accurately evaluate the energy loss E_{loss} by integration, a continuous record of wind speed and direction should be provided for the calculation of power output at any time. Since continuous climatic records are normally unavailable at offshore farm site, hourly averaged wind speed and direction are used to calculate energy loss.

In this study, the scheduling of preventive maintenance is investigated using an hourly time frame. The starting and ending time of maintenance, t_{start} and t_{end}, can be represented by numbers of hours counted from the beginning of a year. The total energy loss during the interval from t_{start} to t_{end} is the sum of hourly energy losses $E_{loss}^{(k)}, k = t_{start}, ..., t_{end}$, which is given by

$$E_{loss} \approx \sum_{k=t_{start}}^{t_{end}} E_{loss}^{(k)}. \tag{8}$$

The minimization of the annual energy loss E_{loss} caused by preventive maintenance is the objective of the schedule optimization problem formulated in Section 3.

3 | OPTIMIZATION PROBLEM OF MAINTENANCE SCHEDULING

3.1 | Analyses of schedule optimization

In this study, the optimization of maintenance schedule is investigated for a 1 year's time span. According to the wind turbine manufacture's manual, preventive maintenance is normally performed twice a year for each turbine.[39] Weather and sea conditions in the region where a wind farm is located are the primary considerations for choosing the time windows for scheduled maintenance.[77] Since spring and autumn are generally comfortable seasons for maintenance personnel to enter offshore site and perform maintenance, it is sensible to arrange the first maintenance in spring and the second in autumn.[78] These two maintenance intervals are not overlapped. Each of the two times of maintenance is performed within a specified time interval. In each interval, it typically takes two to three consecutive days to finish the maintenance activities for one turbine.[79] The requirement of three consecutive days is a prevailing practice. This continuity might be interrupted, especially when maintenance personnel encounter extreme weather conditions or unexpected difficulties. When such interruptions occur, the maintenance of one turbine can be completed within a time frame of more than 3 days, allowing one or more interruptions. It is expected that this relaxation will result in the arrangement of more maintenance work on the days with lower wind speed, thereby reducing downtime energy loss. In this study, the restriction of three consecutive days is enforced to satisfy the common requirement of maintenance personnel.

Limited capacity of labor force, varying wind conditions, and wake effects are the three reasons why schedule optimization is needed to reduce energy loss during maintenance. If labor force is sufficient to perform maintenance for all turbines in a wind farm concurrently, the best time is when wind speed is the lowest in spring interval or autumn interval. The limited capacity of labor force constrains the number of turbines that can be maintained concurrently. Moreover, the shutdown of all turbines in a wind farm at the same time for maintenance results in days of undesirable disruption of power supply. In order to keep the work within the capacity of the labor force and avoid disruption of power supply, schedule optimization is needed to spread out maintenance activities of different turbines over spring interval or autumn interval. If wind conditions are constant during each maintenance interval, neglecting wake effects, the shutdown of any turbine at any time results in the same amount of power reduction. Varying wind conditions provide the opportunity to reduce downtime energy loss by optimally scheduling maintenance activities at the time when wind speed is low. Wind conditions basically determine when to maintain wind turbines. If wake effects are ignored, given the same topography and wind conditions, each turbine of the same type will produce the same amount of power regardless of its location. In this situation, it is pointless to choose turbines for maintenance based on their locations. Optimization can weaken the influence of wake effects by selecting the turbines at suitable locations, and consequentially reduce downtime energy loss.

Since preventive maintenance is performed twice a year for each wind turbine, there are $2N$ maintenance starting time parameters for a wind farm comprising N turbines. The two maintenance starting time parameters for the ith turbine are denoted as t_i and t_{N+i}. They are represented by numbers of hours counted from the beginning of a year, which are integers. The maintenance of each turbine is constrained within a specified time interval. The earliest and the latest available time to start the first maintenance for the ith turbine are, respectively, denoted as $t_i^{earliest}$ and t_i^{latest}. For the second maintenance, they are denoted as $t_{N+i}^{earliest}$ and t_{N+i}^{latest}. These time variables are also expressed as numbers of hours counted from the beginning of a year. During each time interval of maintenance, each turbine is shut down for a specified number of days, which include n consecutive hours. On any day inside each time interval, there can be no turbine, one turbine, or multiple turbines shut down for maintenance. The wind speed and wind direction during these maintenance days are inputs to the power generation model described in Section 2.2, used to calculate downtime energy loss.

3.2 | Constraints for weather conditions and labor force

At an offshore wind farm site, at any time t during maintenance, the relevant weather conditions include

- $v_{wind}(t)$ (unit: m/s): The wind speed at t.
- $v_{gust}(t)$ (unit: m/s): The wind gust at t.
- $T_{air}(t)$ (unit: K): The air temperature at t.
- $h_{wave}(t)$ (unit: m): The significant wave height at t.

Site accessibility and maintenance feasibility of offshore wind farms are significantly constrained by weather conditions. Wind speed, wind gust, air temperature, and significant wave height at offshore site should satisfy safety requirements. When wind speed is higher than 20 m/s, it is not allowed to climb up turbines.[40] For category B vessels to transport maintenance personnel to an offshore site, wind speed should be lower than 20.7 m/s (Beaufort force 8), wind gust should be less than 21 m/s, and significant wave height should be lower than 4 m.[80] According to guidelines for working outdoors, the highest and the lowest air temperatures allowed for outdoor maintenance are 26°C and −26°C, respectively.[81,82] Since preventive maintenance seldom requires cranes or jack-ups, the operation conditions for these tools are not considered.

During maintenance, personnel are exposed to outdoor wind. The rate of heat loss from the human body is the combined effect of low temperature and blowing wind. Wind chill temperature describes how cold skin feels due to the combination of these two types of influences. Its value can be calculated using the formula recommended by the U.S. National Weather Service.[83] Air temperature is converted from Celsius to Fahrenheit using

$$T_{air\_Fahrenheit} = \left(T_{air\_Celsius} \times \frac{9}{5}\right) + 32. \tag{9}$$

Wind speed is converted from meters per second to miles per hour using

$$v_{wind\_mph} = 2.23694 \times v_{wind\_m/s}. \tag{10}$$

Wind chill temperature in Fahrenheit is calculated by

$$T_{WindChill\_Fahrenheit} = 35.74 + 0.6215 \times T_{air\_Fahrenheit} - 35.75 \times v_{wind\_mph}^{0.16} + 0.4275 \times T_{air\_Fahrenheit} \times v_{wind\_mph}^{0.16}. \tag{11}$$

Wind chill temperature in Celsius (converted from $T_{WindChill\_Fahrenheit}$) is also constrained between 26°C and −26°C, the same as the recommended highest and lowest values for working outdoors.

In order to ensure the safety of maintenance personnel during working hours, weather conditions are required to satisfy the lower and upper bounds described below.

- v_{wind}^{lower} and v_{wind}^{upper} (unit: m/s): The lower and upper bounds of wind speed.
- v_{gust}^{lower} and v_{gust}^{upper} (unit: m/s): The lower and upper bounds of wind gust.
- T_{air}^{lower} and T_{air}^{upper} (unit: K): The lower and upper bounds of air temperature.
- $T_{WindChill}^{lower}$ and $T_{WindChill}^{upper}$ (unit: K): The lower and upper bounds of wind chill temperature.
- h_{wave}^{lower} and h_{wave}^{upper} (unit: m): The lower and upper bounds of significant wave height.

Determined by the starting time of maintenance, t_i and t_{N+i}, and the n consecutive hours of maintenance duration, a set of Q days are selected for preventive maintenance. On each maintenance day ($j \in Q$), maintenance personnel start working from t_j and continue working for m hours. During these m hours, weather conditions should satisfy their constraints.

The number of turbines maintained concurrently on the jth day in Q is H_j. Multiple turbines may be maintained on the same day. The number H_j should be less than or equal to the maximum number G of turbines that can be maintained concurrently limited by the capacity of maintenance personnel.

3.3 | Formulation of the optimization problem

Before the formulation of the optimization problem is presented, its design variables, objective, and parameters are listed below.

- $t_1, \ldots t_N, t_{N+1}, \ldots t_{2N}$: The design variables, which are the maintenance starting time for each turbine in the two maintenance intervals. The value N is the total number of wind turbines. In each interval, there are N starting time. Since there are two intervals, there are totally $2N$ starting time. The time t is expressed as the number of hours counted from the beginning of a year.
- E_{loss}: The objective of optimization, which is the total annual downtime energy loss due to shut down of turbines during preventive maintenance.
- i: The number used to denote different turbine in a wind farm. Its range is from 1 to N.
- $t_i^{earliest}$: The earliest available time to start the first maintenance for the ith turbine.
- t_i^{latest}: The latest available time to start the first maintenance for the ith turbine
- $t_{N+i}^{earliest}$: The earliest available time to start the second maintenance for the ith turbine.
- t_{N+i}^{latest}: The latest available time to start the second maintenance for the ith turbine.
- Q: The set of days selected for preventive maintenance.
- j: The number used to donate one of the selected maintenance days ($j \in Q$).
- t_j: The time to start working on the jth maintenance day.
- m: The number of consecutive working hours on each maintenance day.
- $v_{wind}(t)$: The wind speed at time t.
- v_{wind}^{lower}: The lower bound of wind speed.
- v_{wind}^{upper}: The upper bound of wind speed.
- $v_{gust}(t)$: The speed of wind gust at time t.
- v_{gust}^{lower}: The lower bound of wind gust.
- v_{gust}^{upper}: The upper bound of wind gust.
- $T_{air}(t)$: The air temperature at time t.
- T_{air}^{lower}: The lower bound of air temperature.
- T_{air}^{upper}: The upper bound of air temperature.
- $T_{WindChill}(t)$: The wind chill temperature at time t.
- $T_{WindChill}^{lower}$: The lower bound of wind chill temperature.
- $T_{WindChill}^{upper}$: The upper bound of wind chill temperature.
- $h_{wave}(t)$: The significant wave height at time t.
- h_{wave}^{lower}: The lower bound of significant wave height.
- h_{wave}^{upper}: The upper bound of significant wave height.
- H_j: The number of turbines maintained concurrently on the jth day.
- G: The maximum number of turbines that can be maintained concurrently, limited by the capacity of maintenance personnel.

For a given year, to minimize downtime energy loss due to preventive maintenance, the schedule optimization problem is formulated as follows:

$$\min_{t_1,\ldots t_N, t_{N+1},\ldots t_{2N}} E_{loss} \tag{12}$$

subject to

$$t_i^{earliest} \le t_i \le t_i^{latest},\ i = 1,\ldots,N \tag{13}$$

$$t_{N+i}^{earliest} \le t_{N+i} \le t_{N+i}^{latest},\ i = 1,\ldots,N \tag{14}$$

$$v_{wind}^{lower} \le v_{wind}(t) \le v_{wind}^{upper},\ t \in [t_j, t_j + m - 1],\ j \in Q \tag{15}$$

$$v_{gust}^{lower} \le v_{gust}(t) \le v_{gust}^{upper},\ t \in [t_j, t_j + m - 1],\ j \in Q \tag{16}$$

$$T_{air}^{lower} \le T_{air}(t) \le T_{air}^{upper},\ t \in [t_j, t_j + m - 1],\ j \in Q \tag{17}$$

$$T_{WindChill}^{lower} \le T_{WindChill}(t) \le T_{WindChill}^{upper},\ t \in [t_j, t_j + m - 1],\ j \in Q \tag{18}$$

$$h_{wave}^{lower} \le h_{wave}(t) \le h_{wave}^{upper},\ t \in [t_j, t_j + m - 1],\ j \in Q \tag{19}$$

$$0 < H_j \le G,\ j \in Q \tag{20}$$

The schedule optimization problem minimizes downtime energy loss by selecting optimal maintenance time windows. Constraints (13) and (14) require the two maintenance processes of each turbine to start within specified time intervals. The weather conditions during working hours from t_j to $t_j + m - 1$ on maintenance day $j \in Q$ should satisfy constraints (15), (16), (17), (18), and (19). Constraint (20) specifies that the number of turbines being maintained should be within the capacity of maintenance personnel.

The design variables of the optimization problem are integers. The objective function and some of the constraints are nonlinear. The optimization problem is therefore a mixed-integer nonlinear programming problem. Since the computational cost to evaluate the annual energy generation of a wind farm is considerable, an exhaustive search to the optimal solution requires prohibitively expensive computational cost. The discontinuous non-differentiable nonlinear objective function and constraints make it unsuitable for gradient-based approaches to solve such a complex problem. More efficient approaches to solve the optimization problem are preferred. Evolutionary algorithms are a class of population-based heuristic optimization methods. The genetic algorithm[84] is the most widely used in this class. Its procedure of optimization mimics the process of natural selection, such as inheritance, mutation, and crossover. A population of candidate solutions are repeatedly modified until the optimal solution is reached. The genetic algorithm can efficiently solve mixed-integer nonlinear programming problems with discontinuous non-differentiable nonlinear objective function and constraints. There can be multiple local optima for the schedule optimization problem. The genetic algorithm can escape from local optima, and search for a globally optimal solution with acceptable computational cost. Therefore, the genetic algorithm is adopted to solve the optimization problem of maintenance scheduling. Particle swarm optimization, ant colony optimization, and combinatorial Bayesian optimization solvers could also be potentially used to solve mixed-integer nonlinear programming problems.

Since the starting time for the first maintenance, $t_1, \dots t_N$, and the starting time for the second maintenance, $t_{N+1}, \dots t_{2N}$, are two separate sets of design variables, the optimization problem can be divided into two separate ones. One of them only includes $t_1, \dots t_N$ as design variables and optimizes the schedule of the first maintenance. The other only includes $t_{N+1}, \dots t_{2N}$ as design variables and optimizes that of the second maintenance. Under readily satisfied conditions regarding personnel availability and the number of turbines, this optimization separation can be correctly assumed.

The time span of each maintenance interval is mainly determined by the number of turbines and the capacity of maintenance personnel. Each interval should be sufficiently long for the personnel to perform maintenance for all turbines. To optimize maintenance schedule using the formulation presented in this section, the weather for the whole upcoming maintenance interval should be known. Indeed, it is challenging to accurately forecast the weather for such a long period of time, for example, 1 to 2 months. It is still possible to use the weather forecast, combined with past climatic records, to minimize the downtime energy loss during preventive maintenance. Assuming air temperature, wind speed, wind direction, and wave height could be forecast for a maintenance interval with an acceptable accuracy, the schedule of preventive maintenance can be optimized. Today, advanced meteorological models running on supercomputers can forecast 12-day weather with sufficient accuracy. If personnel are able to complete the maintenance of all turbines within 12 days, the schedule optimization presented in this paper can take advantage of long-range weather forecasts and reduce downtime energy loss in practical maintenance planning.

4 | CASE STUDY

In 2010, the Cape Wind project was granted the first commercial offshore lease in the United States. The wind farm was designed to comprise 130 Siemens 3.6 MW offshore wind turbines.[85] The site for the Cape Wind is located at Horseshoe Shoal in Nantucket Sound of Cape Cod in Massachusetts, as shown in Figure 1. Although the project was terminated, the study of its O&M will benefit other commercial offshore wind farm projects. This wind farm is used in this study to show that schedule optimization of preventive maintenance can decrease downtime energy losses by alleviating the influence of wake effects.

The schedule optimization presented in this paper can be applied to the preventive maintenance of any offshore wind farm with any layout. The layout of turbines used in this case study is chosen for the purpose of demonstration. The locations of the 25 turbines with their assigned numbers are shown in Figure 2.

In this case study, the preventive maintenance is performed twice a year, and it takes 3 days to finish the maintenance of each turbine. Considering the climate at Cape Cod, the first maintenance interval is scheduled in March, and the second is in September.

The primary factors that determine the length of each maintenance interval are the number of turbines and the capacity of maintenance personnel. Each interval should include adequate number of days for the personnel to perform maintenance for all turbines. Assuming all maintenance personnel work everyday at full capacity, the smallest required number of days is the shortest maintenance interval. A longer interval can relieve the personnel from working pressure and provide the opportunity to reduce downtime energy loss by arranging maintenance to the days when wind speed is relatively low. The aim of this case study is to demonstrate that an optimized schedule of preventive maintenance considering wind conditions and wake effects can meaningfully reduce downtime energy loss. It is necessary for each interval to include an appropriate number of days that no turbines are under maintenance using an optimized schedule. The wind conditions of the days with no turbine, few turbines, or a large number of turbines under maintenance can be analyzed to show how wind speed, wind direction, and wake effects affect the selection of turbines for maintenance. Considering these factors, 1 month is a reasonable length of time to perform maintenance for 25 turbines in the

FIGURE 1 Map of Cape Wind.[86]

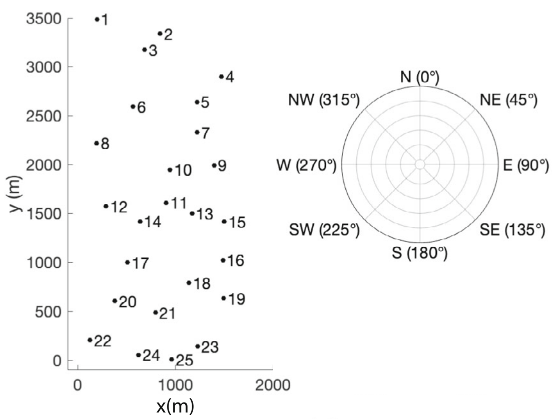

FIGURE 2 Locations of 25 wind turbines.

offshore wind farm. This case study selects the 60th–92nd and the 240th–272nd days in a year as the two maintenance intervals. The starting date for the first maintenance is constrained inclusively between the 60th and the 90th days in a year. The second starting date is constrained inclusively between the 240th and the 270th days. The length of each maintenance interval can be specified by setting the starting time and ending time of the two maintenance intervals, which are constraints (13) and (14) of the optimization problem presented in Section 3. Different sizes of wind farms and various maintenance strategies require different length of maintenance intervals. Other factors affecting the selection of the length of a maintenance interval include transportation, logistics, and agreement with maintenance service providers, which are not explicitly considered in the formulation of optimization problem in this paper.

The climatic conditions at Cape Cod are used to calculate energy production and assess site accessibility. To optimize the maintenance schedule of an offshore wind farm in a given year, the site weather conditions for that year should be obtained. Due to unavailability of weather forecasts, recorded historical hourly climatic data are used. The historical weather data at Cape Cod can be downloaded from the NOAA National Data Buoy Center.[87] The weather conditions during the 60th–92nd and the 240th–272nd days of 2010, 2011, 2015, 2016, and 2019 are reasonably well documented. The annual schedule of preventive maintenance is optimized using the climatic data of each of these 5 years.

On each maintenance day, maintenance personnel work from 9 a.m. to 5 p.m. EST. The number of turbines maintained concurrently on each day is constrained not to exceed 11 because of limited labor force. The maintenance of each turbine can only be performed within a time frame of three consecutive days when site weather conditions during working hours satisfy constraints (15) to (19).

4.1 | Optimization results

The minimization of downtime energy loss and the analyses of how wake effects influence the selection of turbines for maintenance are performed for 2010, 2011, 2015, 2016, and 2019. The optimization results for these 5 years are presented in Table 1. For the purpose of conciseness, only the details and analyses of results for 2019 are presented in this paper. The generated data for all of the 5 years are archived at the address specified in the section of Data Availability Statement at the end of this paper.

The minimization of downtime energy loss is performed by selecting optimal maintenance time windows for turbines. The genetic algorithm iterates through generations to minimize annual downtime energy loss. Each generation contains a population of candidates. The minimum value of a generation is the lowest annual downtime energy loss of the population, while the mean value is the average of the population. Figure 3 shows the minimum values and the mean values of annual downtime energy loss considering wake effects in the generations before reaching the optimal result for 2019.

This case study aims to show how the downtime energy loss of an offshore wind farm subjected to wake effects can be minimized by optimizing maintenance schedule. In order to quantitatively assess the amount of downtime energy saved due to consideration of wake effects, two forms of optimization are performed and their results are compared. The first form *considers* wake effects, and uses the power generation model described in Section 2.2 to evaluate the energy production of the entire wind farm. The second form of optimization completely *ignores* wake effects, and the energy generation of a wind farm is simply the sum of each turbine evaluated using its power curve. Both forms use the same

TABLE 1 Optimization results for five different years *considering* wake effects.

Year	Number of Generations	Minimized energy loss (MWh)	First average (MWh)	Saved energy (MWh)	Saved percentage	Annual power (MW)	Equivalent hours	Percentage of annual energy	Saved money (USD)
2010	143	5.189×10^3	7.700×10^3	2.511×10^3	32.61%	55.49	45.25	0.52%	5.60×10^5
2011	126	6.194×10^3	8.269×10^3	2.075×10^3	25.09%	54.08	38.37	0.44%	4.63×10^5
2015	318	6.017×10^3	8.019×10^3	2.002×10^3	24.97%	52.02	38.48	0.44%	4.47×10^5
2016	265	5.228×10^3	7.831×10^3	2.603×10^3	33.24%	57.49	45.27	0.52%	5.81×10^5
2019	291	6.103×10^3	8.283×10^3	2.180×10^3	26.32%	55.57	39.23	0.45%	4.87×10^5

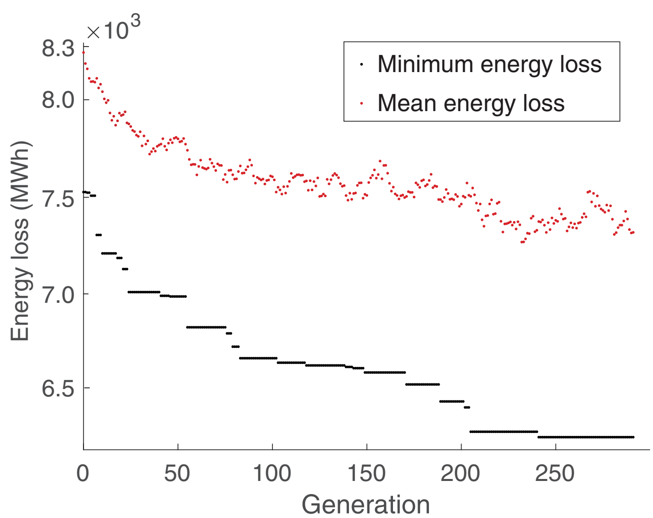

FIGURE 3 Minimization of annual downtime energy loss in 2019 using the genetic algorithm.

formulation of schedule optimization presented in Section 3. The only difference is whether wake effects are taken into account in evaluating wind power.

After both forms of optimization are performed, two optimized maintenance schedules are achieved, respectively *considering* and *ignoring* wake effects. Please note that the second form of schedule optimization *ignores* wake effects, but, after the second optimized schedule is obtained, the evaluation of downtime energy loss using the second schedule should *consider* wake effects. The values of downtime energy loss for these two different optimized schedules need to be calculated taking wake effects into account. The difference of these two values is the annual downtime energy loss reduced due to the consideration of wake effects in the schedule optimization.

Both forms of optimization (*considering* and *ignoring* wake effects) are performed for five different years. Their results are separately presented in Tables 1 and 2. The two tables have the same layout.

- **Column 1:** Which year the optimization of maintenance is performed for.
- **Column 2:** How many generations the genetic algorithm has iterated before reaching the optimal solution presented in column 3.
- **Column 3:** The minimized downtime energy loss corresponding to the optimal maintenance schedule.
- **Column 4:** The average downtime energy loss of the first generation of the genetic algorithm, using a random maintenance schedule.
- **Column 5:** Compared with the average downtime energy loss of the first generation (column 4), how much energy the minimized (column 3) has saved.
- **Column 6:** The percentage that represents the ratio of the saved energy (column 5) to the average of the first generation (column 4).
- **Column 7:** The annual average power generated by the entire wind farm using the optimal maintenance schedule.
- **Column 8:** How many hours of annual average power (column 7) are equivalent to the saved energy (column 5).
- **Column 9:** The percentage that represents the ratio of the saved downtime energy (column 5) to the annual energy production of the wind farm.
- **Column 10:** How much money is equivalent to the saved energy (column 5), evaluated using the price of 22.32 cents per kWh, which is the price of residential electricity in Massachusetts in January 2021.

Observed from Table 1, *considering* wake effects, approximately 25% to 33% of downtime energy loss is reduced in each year through the optimization of maintenance schedule, compared with the average energy loss of the first generation using a random maintenance schedule. The annual saved downtime energy is equivalent to approximately 40 hours of average power produced by the entire wind farm. The price of the annual saved energy through optimization is in the neighborhood of half a million US dollars.

Table 2 shows the results if wake effects are *ignored* in the process of schedule optimization. The saved downtime energy for each year if wake effects are *ignored* is less than their corresponding values in Table 1 when wake effects are *considered*. The difference is the energy saved annually due to consideration of wake effects, which is shown in the second column of Table 3. In Table 3, the value of annual saved energy due to consideration of wake effects (column 2) is measured by its equivalent hours (column 3) of average power produced by the entire wind farm, the percentage of annual energy production (column 4), and the cost of electricity fee (column 5). The annual downtime energy loss reduced due to consideration of wake effects is approximately 5 to 16 hours of wind farm power generation, which is 0.07% to 0.19% of the annual farm energy production. It saves approximately 70,000 to 190,000 USD of electricity fee annually, which is a considerable amount of profit.

The turbines under maintenance on each day during the spring interval and autumn interval in 2019 are shown in Tables 4 and 5. Column 1 shows the number of days counting from the beginning of the year. The daily average wind speed is given in column 2. The turbines selected for maintenance are listed in column 3. Column 4 presents the 11 turbines with lowest daily energy productions assuming all turbines are operating, ordered from the lowest to higher. Column 5 evaluates the daily downtime energy loss due to preventive maintenance. The wind speed and the number of turbines maintained on each day during the spring interval and autumn interval in 2019 are plotted in Figure 4A,B. The optimized maintenance schedules of the other 4 years are presented in the file archived at the address specified in the section of Data Availability Statement at the end of this paper. Since low wind speed generally generates low wind power, it reduces downtime energy loss to maintain turbines during

TABLE 2 Optimization results for five different years *ignoring* wake effects.

Year	Number of Generations	Minimized energy loss (MWh)	First average (MWh)	Saved energy (MWh)	Saved percentage	Annual power (MW)	Equivalent hours	Percentage of annual energy	Saved money (USD)
2010	225	5.966×10^3	7.700×10^3	1.734×10^3	22.52%	55.40	31.30	0.36%	3.87×10^5
2011	212	6.548×10^3	8.269×10^3	1.721×10^3	20.81%	54.04	31.85	0.36%	3.84×10^5
2015	255	6.870×10^3	8.019×10^3	1.149×10^3	14.33%	51.93	22.13	0.25%	2.56×10^5
2016	345	5.553×10^3	7.831×10^3	2.278×10^3	29.09%	57.46	39.65	0.45%	5.08×10^5
2019	367	6.917×10^3	8.283×10^3	1.366×10^3	16.49%	55.48	24.62	0.28%	3.05×10^5

TABLE 3 Downtime energy reduced due to consideration of wake effects for five different years.

Year	Saved energy (MWh)	Equivalent hours	Percentage of annual energy	Saved money (USD)
2010	7.77×10^2	14.00	0.16%	1.73×10^5
2011	3.54×10^2	6.55	0.08%	0.79×10^5
2015	8.53×10^2	16.40	0.19%	1.90×10^5
2016	3.25×10^2	5.65	0.07%	0.73×10^5
2019	8.14×10^2	14.65	0.17%	1.82×10^5

TABLE 4 Turbines maintained during the spring interval in 2019.

Day	Wind speed (m/s)	Turbines under maintenance	Turbines with least energy production	Energy loss (kWh)
60	2.2	1, 4, 7, 10, 11, 17, 24	19, 25, 13, 16, 18, 23, 21, 15, 11, 9, 24	4.753×10^4
61	8.6	1, 4, 7, 10, 11, 17, 24	22, 14, 20, 17, 21, 12, 11, 3, 25, 24, 10	4.596×10^5
62	3.2	1, 4, 7, 10, 11, 17, 24	19, 16, 13, 25, 15, 18, 9, 7, 11, 21, 14	1.379×10^5
63	8.0	None	13, 25, 19, 11, 16, 18, 15, 14, 21, 9, 10	0
64	7.3	None	16, 15, 9, 19, 13, 18, 25, 23, 11, 4, 7	0
65	8.7	None	15, 19, 16, 25, 13, 9, 18, 23, 4, 14, 21	0
66	8.5	25	15, 25, 19, 13, 16, 14, 4, 21, 18, 24, 7	8.281×10^4
67	7.3	25, 6, 8	15, 16, 19, 25, 13, 9, 18, 23, 4, 11, 5	2.208×10^5
68	3.1	25, 6, 8, 14, 18	16, 15, 11, 18, 9, 13, 23, 19, 25, 7, 14	8.593×10^4
69	9.0	6, 8, 14, 18	12, 22, 14, 11, 20, 24, 17, 10, 18, 8, 21	2.141×10^5
70	4.7	14, 18, 5	9, 16, 7, 15, 11, 4, 2, 10, 18, 13, 23	9.194×10^4
71	5.3	5, 2, 9, 13, 23	15, 19, 16, 25, 13, 18, 9, 14, 4, 23, 21	2.596×10^5
72	3.6	5, 2, 9, 13, 23, 12	16, 19, 13, 15, 9, 7, 18, 25, 11, 23, 10	1.149×10^5
73	3.8	2, 9, 13, 23, 12	5, 7, 10, 3, 9, 6, 2, 11, 14, 15, 8	8.676×10^4
74	8.7	12	7, 10, 6, 5, 3, 17, 14, 13, 11, 8, 12	8.002×10^4
75	6.7	None	15, 16, 9, 13, 19, 7, 18, 11, 25, 4, 5	0
76	8.3	None	15, 16, 19, 25, 13, 9, 18, 23, 4, 5, 14	0
77	6.5	16, 21	16, 19, 15, 25, 13, 9, 18, 23, 11, 21, 5	1.389×10^5
78	3.9	16, 21, 15, 19	15, 16, 13, 19, 9, 25, 18, 23, 11, 7, 4	1.288×10^5
79	4.0	16, 21, 15, 19	15, 7, 9, 16, 5, 13, 10, 11, 19, 18, 14	1.027×10^5
80	6.0	15, 19	12, 11, 5, 10, 14, 7, 3, 6, 8, 17, 13	1.194×10^5
81	9.2	None	19, 25, 16, 13, 15, 18, 9, 21, 11, 23, 24	0
82	12.4	None	15, 25, 19, 16, 13, 9, 18, 4, 14, 23, 21	0
83	8.8	None	16, 9, 15, 23, 11, 18, 13, 2, 4, 19, 7	0
84	5.1	None	11, 18, 14, 13, 25, 16, 20, 22, 15, 19, 21	0
85	5.7	3, 20	22, 20, 17, 11, 24, 14, 18, 23, 25, 21, 12	9.905×10^4
86	6.1	3, 20	22, 20, 17, 14, 11, 24, 12, 25, 21, 18, 13	9.964×10^4
87	5.7	3, 20, 22	5, 7, 10, 14, 3, 15, 4, 9, 11, 13, 6	1.471×10^5
88	6.6	22	7, 5, 10, 4, 15, 9, 11, 14, 2, 16, 13	6.848×10^4
89	3.6	22	5, 7, 10, 11, 14, 3, 9, 6, 15, 13, 17	3.068×10^4
90	8.9	None	15, 7, 19, 4, 16, 10, 13, 9, 2, 14, 5	0
91	9.2	None	19, 15, 25, 16, 13, 18, 9, 21, 23, 14, 5	0
92	4.9	None	19, 13, 25, 16, 18, 15, 11, 7, 9, 5, 21	0
Sum				2.817×10^6

TABLE 5 Turbines maintained during the autumn interval in 2019.

Day	Wind speed (m/s)	Turbines under maintenance	Turbines with least energy production	Energy loss (kWh)
240	5.0	1, 9	5, 11, 12, 7, 8, 3, 10, 6, 14, 17, 2	7.434×10^4
241	5.9	1, 9	5, 7, 11, 10, 14, 13, 18, 15, 16, 9, 17	1.068×10^5
242	6.2	1, 9, 3, 15	15, 16, 19, 13, 25, 9, 18, 7, 23, 4, 5	2.304×10^5
243	3.9	3, 15, 7, 12, 23	19, 16, 13, 25, 18, 15, 11, 9, 23, 21, 7	1.469×10^5
244	5.0	3, 15, 7, 12, 23, 11	22, 20, 14, 12, 17, 11, 21, 24, 25, 18, 10	2.571×10^5
245	5.1	7, 12, 23, 11	5, 10, 11, 12, 3, 7, 14, 6, 8, 17, 13	1.547×10^5
246	5.1	11, 2	18, 19, 11, 16, 25, 13, 23, 20, 21, 7, 14	8.604×10^4
247	5.7	2, 13	5, 7, 10, 11, 3, 6, 14, 12, 9, 8, 17	1.092×10^5
248	5.7	2, 13, 5, 6, 8, 20	25, 20, 11, 22, 18, 14, 19, 21, 23, 17, 13	2.995×10^5
249	8.0	13, 5, 6, 8, 20	14, 21, 22, 3, 20, 25, 12, 17, 10, 18, 8	2.464×10^5
250	12.6	5, 6, 8, 20	19, 16, 25, 13, 15, 18, 9, 23, 7, 11, 21	1.013×10^5
251	8.1	25	15, 16, 9, 13, 19, 25, 23, 18, 11, 4, 7	7.133×10^4
252	4.9	25, 21, 24	22, 14, 12, 20, 11, 25, 24, 17, 21, 18, 13	1.282×10^5
253	3.9	25, 21, 24	12, 11, 8, 20, 17, 22, 1, 13, 6, 14, 18	7.194×10^4
254	8.5	21, 24	5, 7, 10, 3, 9, 14, 15, 2, 6, 11, 8	1.664×10^5
255	7.5	None	16, 9, 11, 15, 23, 13, 18, 7, 10, 19, 2	0
256	8.6	None	22, 20, 17, 14, 11, 21, 24, 25, 12, 10, 3	0
257	7.8	None	5, 12, 11, 7, 10, 14, 3, 8, 22, 6, 17	0
258	6.2	17	15, 16, 9, 7, 13, 4, 11, 19, 18, 10, 5	6.216×10^4
259	5.2	17	19, 25, 16, 13, 18, 23, 11, 15, 21, 20, 14	4.331×10^4
260	6.6	17	19, 25, 16, 18, 22, 13, 20, 21, 23, 24, 17	6.503×10^4
261	9.0	None	22, 20, 17, 14, 21, 11, 24, 25, 10, 3, 8	0
262	7.6	10, 14	23, 20, 22, 25, 19, 18, 24, 17, 21, 11, 13	1.313×10^5
263	4.5	10, 14, 4, 16, 18, 19	15, 16, 13, 9, 19, 25, 11, 18, 23, 7, 4	2.117×10^5
264	3.8	10, 14, 4, 16, 18, 19	15, 16, 19, 13, 25, 9, 18, 23, 11, 7, 5	1.871×10^5
265	5.2	4, 16, 18, 19	7, 9, 4, 11, 10, 15, 2, 16, 18, 13, 19	1.726×10^5
266	9.0	None	16, 7, 9, 11, 2, 4, 15, 10, 18, 23, 19	0
267	6.8	None	15, 16, 9, 13, 11, 19, 18, 23, 7, 4, 25	0
268	6.1	None	16, 19, 15, 9, 25, 13, 18, 23, 11, 21, 7	0
269	6.4	22	7, 15, 9, 16, 11, 4, 10, 2, 13, 18, 19	6.078×10^4
270	5.3	22	19, 16, 13, 25, 15, 18, 7, 9, 11, 23, 21	5.084×10^4
271	6.0	22	7, 10, 4, 15, 9, 11, 5, 14, 2, 13, 16	5.065×10^4
272	7.1	None	22, 16, 20, 15, 11, 25, 19, 13, 18, 9, 23	0
Sum				3.286×10^6

the time of low wind speed. The optimized schedules for all the 5 years verify that the optimal time windows for maintenance are generally on the days of low wind speed.

4.2 | Classification of turbines under maintenance

The days with relatively large numbers of turbines under maintenance are chosen to investigate how the distribution of hourly wind speed and direction affects the optimal selection of turbines for maintenance. In each of the two maintenance intervals in 2010, 2011, 2015, 2016, and

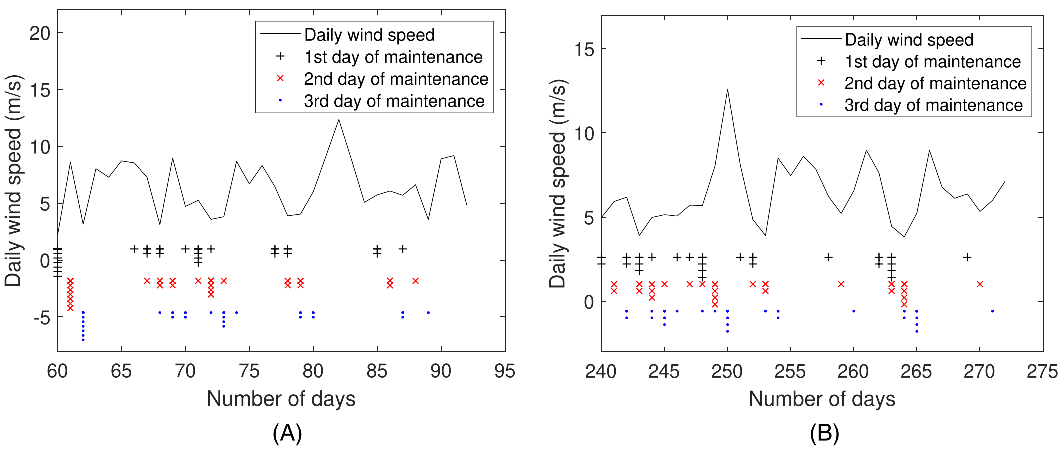

FIGURE 4 Two maintenance intervals in 2019. (A) Spring interval in 2019. (B) Autumn interval in 2019.

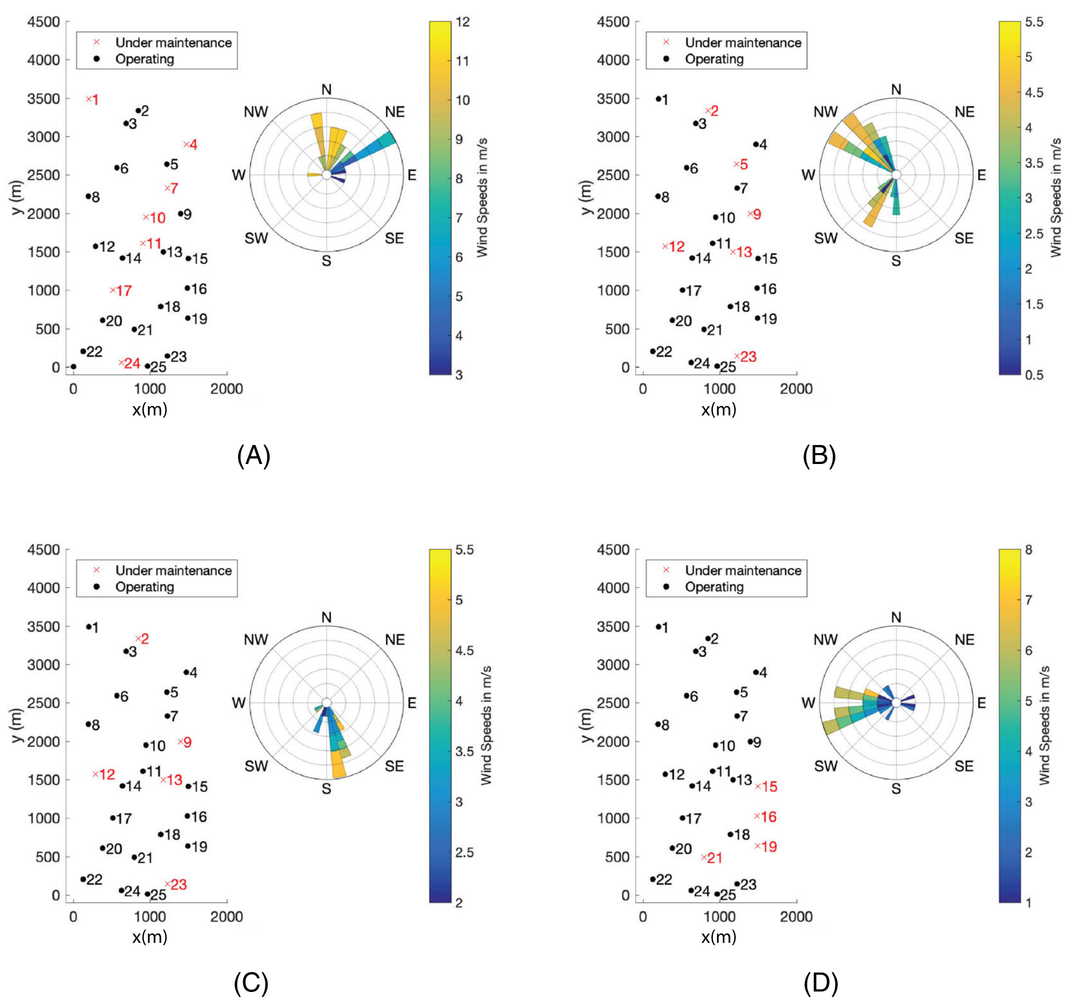

FIGURE 5 Locations of the turbines under the first maintenance in Spring 2019. (A) The 61st day in 2019. (B) The 72nd day in 2019. (C) The 73rd day in 2019. (D) The 78th day in 2019.

2019, 4 days are chosen to study the selection of turbines. The locations of the turbines under maintenance on the selected days, as well as wind roses, are shown on figures. For the purpose of conciseness, only the figures for 2019 are presented in this paper. The figures for other years can be found in the file archived at the address specified in the section of Data Availability Statement at the end of this paper.

Figures 5A to 6D show the turbines under maintenance on the eight days specified by the titles of these figures. The turbines represented by red crosses and labeled with red numbers are under maintenance. The operating turbines are represented by black dots and labeled with black numbers. Wind roses are circular charts used to characterize the wind speeds, directions, and frequencies over a specified period of time at a location. It composes a number of spokes coming out from the center point of a wind rose. The length of each spoke indicates the amount of time that the wind blows from the direction that the spoke is located. Colors along the spokes represent the categories of wind speed.

As long as wind speed is not zero, any wind turbine generates a wake. The strength, direction, and coverage of the wake are determined by turbine dimensions and wind conditions. In a wind farm, depending on the coverage of wakes, the wake generated by a turbine might influence its downstream ones, and at the same time the turbine might be influenced by its upstream wakes. Since wind direction changes, the relative location (upstream or downstream) between any two turbines in wind flow might vary at different time. At a specific time, supposing all turbines in a wind farm are running, depending on wind direction and turbine locations, the turbines can be generally classified into three categories as shown below. The classification of a turbine is determined by the comparison between the collective wake influence of its upstream ones and the strength that its own wake affects downstream ones.

- **Category I:** The turbines mainly affected by the wakes of upstream ones.
- **Category II:** The turbines mainly producing wakes on downstream ones.
- **Category III:** The turbines both affected by the wakes of upstream ones and producing wakes on downstream ones.

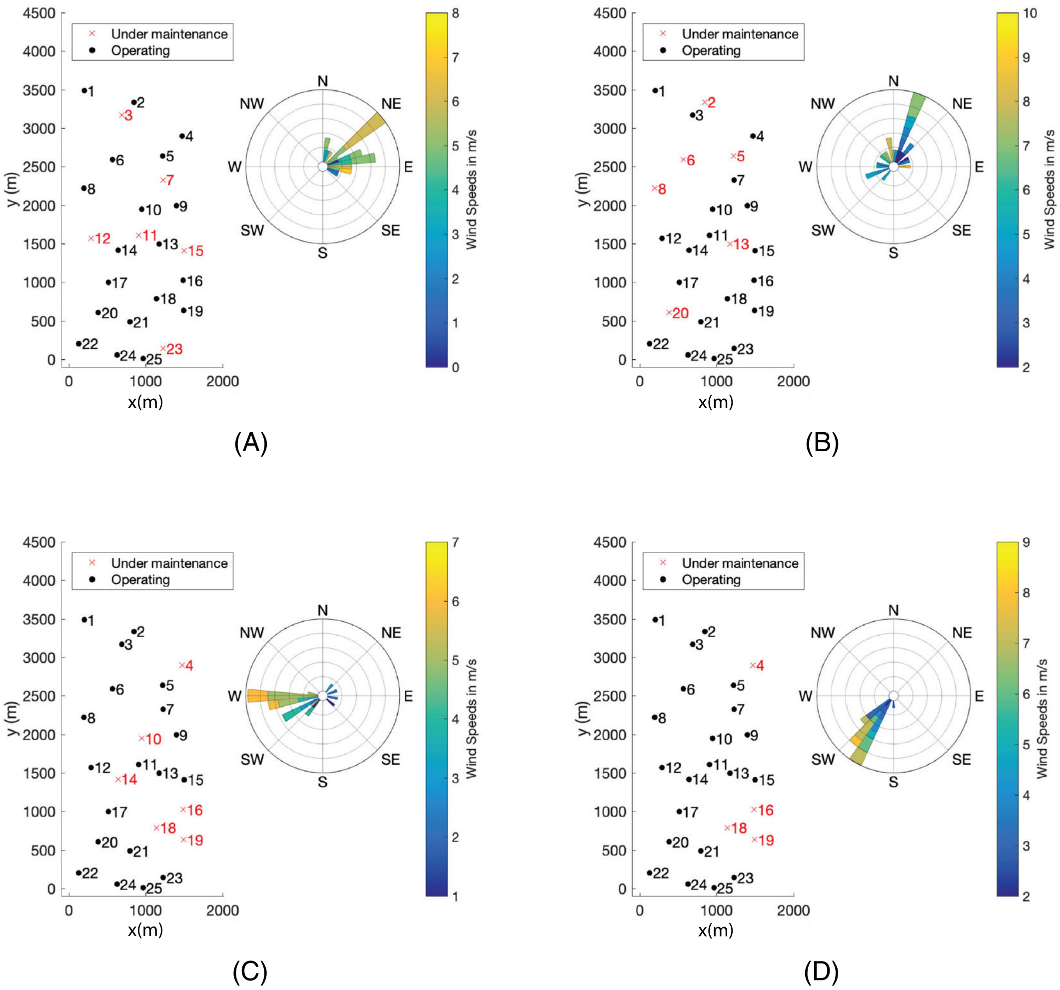

FIGURE 6 Locations of the turbines under the second maintenance in Autumn 2019. (A) The 244th day in 2019. (B) The 248th day in 2019. (C) The 263rd day in 2019. (D) The 265th day in 2019.

TABLE 6 Classification of turbines under maintenance on typical maintenance days in 2019.

Day	Category I	Category II	Category III
61	24	1, 4	7, 10, 11, 17
72	2, 9	12	5, 13, 23
73	2	23	9, 12, 13
78	15, 16, 19	None	21
244	3, 12	7, 15, 23	11
248	None	2	5, 6, 8, 13, 20
263	4, 16, 19	None	10, 14, 18
265	4, 16, 19	None	18

Turbines near the boundary of a wind farm are likely to be classified into Category I or II, when wind direction is near perpendicular to the boundary. For example, when wind blows from east to west, the wake of turbine 8 does not influence any other turbine since it is on the west boundary of the wind farm, and it might be in the wakes of other upstream turbines. In this situation, it belongs to Category I. When wind direction is from west to east, turbine 8 is not in the wake of any other turbine, and its wake might influence others. Accordingly, it belongs to Category II. The situations of the turbines surrounded by others are complicated. Each of them might be influenced by the wakes produced by multiple upstream turbines, and its own wake might impact others in its downstream. Depending on the strength of others' wakes and its own, the turbine might belong to any of the three categories.

Observed from the daily wind rose maps, most maps have one dominant wind direction, and a few have two. The daily dominant wind direction primarily determines which category a turbine belongs to on that day. On different days, it is very likely that the dominant wind direction changes, and consequently the category that a turbine belongs to also changes. As shown in Figures 5B,C and 6A, turbine 12 is under maintenance on the 72nd, 73rd, and 244th days in 2019. On the 3 days, the dominant wind directions shown in their wind rose maps are different. On the 72nd day, wind blows dominantly from northwest and sometimes from southwest. Turbine 12 is generally in the upstream and generates wakes on other turbines. Therefore, it belongs to Category II. On the 73rd day, wind blows from south to north. Turbine 12 is in the downstream of the turbines located in the south of the wind farm, and it is also in the upstream of the turbines located in the north. So, it belongs to Category III. On the 244th day, wind blows dominantly from northeast. Turbine 12 is in the downstream of several turbines, and there is no turbine in its downstream. Hence, it belongs to Category I.

If the first category of turbines are under maintenance, their shutdown generally leads to less reduction in power output of the entire wind farm than the others. If the second category of turbines are shut down, the energy generation of other turbines in their wakes will increase. The shutdown of the third category of turbines will benefit from both less impact on power generation and increasing power of others in their wakes.

Based on careful observation, Table 6 classifies the turbines under maintenance shown in Figures 5A to 6D into the three categories. The classification of the turbines under maintenance on typical days in 2010, 2011, 2015, 2016, and 2019 is shown in a table in the file archived at the address specified in the section of Data Availability Statement at the end of this paper. The classification is based on the major roles of the turbines. After observation of the selection of turbines for maintenance in all 5 years, it is found that on the days with few turbines under maintenance, these turbines mostly belong to Category I or Category II, while on the other days with large numbers of turbines under maintenance, the majority of them belong to Category III.

The discussion of how wake effects affect the selection of turbines for maintenance is based on careful observation of the optimization results. Future research should explore how wind conditions quantitatively affect the selection of turbines for maintenance considering wake effects. Criteria should be created to classify the turbines based on precise calculation of interactions between them due to wake effects.

5 | CONCLUDING REMARKS

This study developed an approach to optimally schedule preventive maintenance of an offshore wind farm influenced by wake effects. A schedule optimization problem was formulated to select time windows for turbine maintenance. Its objective is to minimize annual downtime energy loss due to preventive maintenance. Site accessibility and maintenance feasibility are constrained by site weather conditions. In order to accurately evaluate downtime energy losses, the power generation model used in this study takes wake effects into account. The schedule optimization was performed for a simulated utility-scale offshore wind farm using historical climatic records. The optimal selection of when and which turbines to maintain is mainly determined by wind conditions. Results showed that the downtime energy loss was significantly reduced through the schedule optimization. For the offshore wind farm used for the case study, compared with the downtime energy loss using a random maintenance schedule, the optimized schedule reduced downtime energy loss by approximately 30% annually. This reduction accounts for about 0.5% of annual energy production, and is equivalent to a profit increase of around half million US dollars. A portion of these energy gains were attributed to reduction in overall wake effects by optimally selecting turbines for maintenance, in response to changing wind speed and direction. This portion of energy loss reduced due to consideration of wake effects in each year is approximately 0.07% to 0.19% of the annual energy production. Future research should consider other factors influencing the selection of turbines for maintenance, such as routing of a vessel fleet, scheduling of crew members, and transportation of spare parts. A next-level optimization of maintenance schedule, subject to these additional constraints, could be implemented to further explore reduction of downtime losses and improve profitability.

AUTHOR CONTRIBUTIONS

Junqiang Zhang performed the conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, and writing. Souma Chowdhury performed the conceptualization and software. Jie Zhang performed the conceptualization, methodology, and writing. Weiyang Tong performed the investigation and resources. Achille Messac performed the conceptualization, funding acquisition, supervision, and project administration.

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CONFLICT OF INTEREST STATEMENT

The authors declare no potential conflict of interests.

DATA AVAILABILITY STATEMENT

The data presented in this study are openly available in GitLab at https://gitlab.com/junqiangzhang/wind-farm-maintenance.

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