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Maintenance Activities Coordination for Offshore Wind Farms Integrating Multivariate Stochastic Models

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ABSTRACT: The efficiency and reliability of offshore wind farms are significantly influenced by their maintenance strategies. Effective maintenance coordination is crucial to minimize downtime and consequently maximize reliability. This paper proposes a methodology for integrating multivariate stochastic models into the maintenance scheduling process of offshore wind farms, enabling a more data-driven approach. The proposed framework accounts for the temporal and spatial dependencies of wind variations to optimize maintenance activities, ensuring minimal disruptions to energy production using the Expected Energy Not Supplied (EENS) indicator. We validate our approach using case studies that demonstrate its effectiveness through a sensitivity analysis. The results highlight more than 6% deviations in the EENS estimate for scenarios with the same conditions, where the only difference is the wind speed simulation approach. The change in approach impacts the overall allocation of maintenance activities to offshore wind farms.

1 INTRODUCTION

Offshore wind energy has emerged as a key player in the global transition towards renewable energy [4]. Over the past decade, offshore wind installations have grown rapidly, with global capacity surpassing 67.4 GW by 2024 [16], and projections indicate continued expansion, particularly in regions such as the North Sea and the East China Sea. This growth is driven by the advantages of offshore wind over onshore alternatives, higher and more consistent wind speeds, reduced land use conflicts, and proximity to densely populated coastal demand centers.

Despite its advantages, such as higher wind speeds and reduced land use constraints, offshore wind farms face significant operational challenges, particularly harsh marine conditions, such as high winds, waves, corrosion, and limited accessibility, creating a complex and costly environment for maintenance activities. In addition, accessing offshore turbines often requires specialized vessels, helicopters, or remotely operated vehicles, with substantial logistical planning. This not only inflates costs but also introduces high operational uncertainty, as weather windows narrow and delays become frequent. The harsh marine environment and unpredictable wind conditions complicate preventive and corrective maintenance operations. Unscheduled maintenance interventions can lead to prolonged downtimes and high logistical costs, making efficient maintenance scheduling essential [1].

Current maintenance strategies typically combine preventive maintenance, which follows scheduled intervals but can lead to unnecessary interventions; corrective maintenance, which addresses failures as they occur, often resulting in prolonged downtime and high reactive costs; and condition-based and predictive maintenance, which utilize sensor data and machine learning to forecast failures, reducing unexpected outages and improving reliability.

However, even the most advanced strategies often rely on deterministic models that do not fully incorporate the stochastic, spatio-temporal nature of offshore wind conditions. This omission can significantly undermine planning accuracy. For example, variability in wind speed and direction, and their correlation between spatially distributed turbines, has a positive impact on energy production and accessibility, although these are often oversimplified in existing models [2].

As offshore wind farms scale in size and number, the complexity of coordinating maintenance schedules between multiple geographically dispersed units increases. There is a pressing need for integrated probabilistic decision-making frameworks that account for environmental uncertainty, asset conditions, and system-level constraints.

This paper addresses this need by proposing a methodology that incorporates multivariate stochastic wind modeling into the offshore maintenance scheduling process. The approach accounts for both temporal and spatial wind dependencies and introduces more realism into the simulation of wind behavior. Using the Expected Energy Not Supplied (EENS) as a reliability indicator, the framework is validated through sensitivity analysis and case studies. Ultimately, the goal is to minimize downtime, enhance system reliability, and enable smarter data-driven maintenance planning. This paper proposes a revised methodology for coordinating offshore wind farms' maintenance activities that leverages multivariate stochastic wind modeling to account for a more real-driven approach, introducing new considerations into the modeling process. The methodology, subject to review, is taken from [3], and the study presented in this article aims to address the following key research questions.

How can multivariate stochastic wind models be effectively integrated into maintenance decision-making?

What are the potential impacts of integrating multivariate stochastic wind models on offshore wind farm maintenance scheduling?

How does the proposed approach compare with existing maintenance optimization strategies in terms of results?

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on maintenance planning and stochastic wind modeling, and at the end of the section, the proposed methodology and the new considerations addressed in this contribution are presented. Section 3 presents the parameterization, results and discussion of the optimization solution for the case study, and Section 4 concludes with recommendations for future research.

2 MATERIALS AND METHODS

The maintenance of offshore wind farms has been extensively studied in the literature, with a strong emphasis on preventive and predictive maintenance strategies [5]. First, this section reviews existing work on maintenance planning for offshore wind farms and highlights the role of stochastic wind modeling in improving modeling and, consequently, decision making. Then, knowing that the scale of offshore wind farms is increasing daily and, certainly, the complexity of coordinating maintenance schedules across multiple geographically dispersed units increases, we present a revised methodology with new considerations that proposes an integrated probabilistic decision-making framework that accounts for environmental uncertainty, asset conditions, and system-level constraints.

2.1 *Review of the literature*

Maintenance strategies have been proposed to optimize offshore wind farm operations, mainly preventive maintenance [7], predictive maintenance [5], and condition-based maintenance [6]. As we know, preventive maintenance schedules interventions based on fixed time intervals, reducing unexpected failures, but potentially leading to unnecessary service. Predictive maintenance predicts the remaining useful life of the equipment to anticipate potential failures, enabling early detection of problems and timely maintenance actions. Condition-based maintenance uses real-time sensor data and predictive analytics to schedule interventions based on actual component conditions. Certainly, the most recent state-of-the-art in this domain is the integration of these strategies. For example, studies have shown that condition-based maintenance significantly improves operational efficiency by reducing unnecessary maintenance actions and increasing turbine availability [8]. However, these approaches (preventive, predictive, and condition-based) often neglect the stochastic nature of offshore wind conditions, which can affect accessibility and the feasibility of scheduled maintenance operations.

Stochastic modeling of wind speed and turbulence plays a crucial role in offshore wind energy forecasting and decision making. Traditional wind forecasting models rely on deterministic methods, which do not capture the spatial-temporal uncertainties of offshore wind patterns. On the contrary, stochastic models, such as Markov processes, autoregressive integrated moving average (ARIMA) models and Gaussian mixture models, have been employed to provide probabilistic wind forecasts [9].

Multivariate stochastic models extend these approaches by considering the correlations between different environmental variables, such as wind speed, wind direction, and wave height. This improves predictive accuracy and allows for more robust maintenance planning [10]. For example, recent research has shown that integrating these models into offshore wind maintenance scheduling can improve accessibility predictions and optimize vessel dispatch planning [11].

Studies have explicitly incorporated multivariate stochastic wind modeling into maintenance coordination frameworks. Existing research focuses primarily on single-variable wind speed forecasts, neglecting interactions between wind, wave conditions, and turbine reliability metrics. The need for an integrated approach that captures these dependencies is evident, particularly for offshore wind farms, where accessibility constraints are highly dependent on weather [12].

Recent advances in probabilistic optimization have shown promise in addressing these challenges. Methods such as Monte Carlo simulations, Bayesian inference, and reinforcement learning have been applied to improve maintenance decision making under uncertainty [13]. However, there is still a gap in integrating these approaches with multivariate stochastic wind models to develop a fully adaptive and proactive maintenance framework.

The reviewed literature highlights the interest in optimizing offshore wind farm maintenance through predictive and data-driven approaches. However, there remains a lack of comprehensive frameworks that integrate multivariate stochastic wind models into maintenance coordination.

2.2 *Contribution of this paper.*

This paper aims to contribute by presenting a revised methodology that uses multivariate probabilistic modeling techniques to improve the maintenance scheduling modeling process. As previously highlighted, the methodology, subject to review, is taken from [3]. However, in this section, we present how the new consideration, essentially multivariate stochastic wind modeling, is incorporated into the existing methodology.

Figure 1 shows the revised flow diagram of the optimization problem. Now, the wind energy and thermal units are explicitly separated, although all the generation units are aggregated at the system level. As we can see in Figure 1, the heuristic optimization algorithms propose a set of $x_i = M_{i,1}$ starting maintenance activity time for each generator unit considered in the system, given the constraints of the simulation window. The remaining parameters needed to simulate the stochastic capacity of the units are directly sourced from a SQL (Structured Query Language) database.

Specifically, in the case of wind energy, we introduce in this contribution a modeling change, which aims to consider correlations in the wind speed simulation. Essentially, considering correlations in wind speed simulation means that the wind speed characteristic in a region of the offshore wind farm is homogeneous and that all wind turbines should deliver a similar energy path. As we know, in the case of wind energy, the primary source of energy is the wind, so it is necessary first to simulate the wind speed and then, using the characteristic function of the wind turbine, translate the wind speed into energy.

In this research, we simulate the most likely wind speed v with a Weibull model, estimating the shape and scale parameters of the probability distribution function with the mean and standard deviation of the historical wind speed characteristics of the region. Once the Weibull distribution is parameterized, the inverse cumulative distribution function is used to simulate the wind speed values v by generating uniform random numbers u with (1).

$$v = \delta\left[-\ln(u)\right]^{1/\beta} \tag{1}$$

where v is the wind speed, β and δ are the shape and scale parameters of the Weibull probability distribution function, and u is a uniform random number between [0, 1].

As we can see, the number of random numbers u to be generated depends on $t = 1, 2, \ldots, T$, which is the hourly simulation window.

Regardless of how the correlations can be measured, we intend to assess the impact of correlated wind speed simulations on the risk indicators of the system, specifically assessing the disruptions to energy production using the Expected Energy Not Supplied (EENS) indicator, and eventually in the maintenance scheduling activities to be conducted in the offshore wind farms.

In this paper, we use the Gaussian elliptical copula to simulate uniformly correlated samples U. In the Gaussian copula, the correlation parameter ρ controls the dispersion of random values. Certainly, values of ρ close to one mean more correlated marginals and more homogeneous wind speed simulations. In Section 3, we illustrate the impact of highly correlated wind speed simulations on the wind farm delivery energy path.

As we may know, copula functions try to capture the dependence between marginals through the copula parameter. Certainly, each density may have a different operating space. In the case of the Archimedean copulas, the parameter manages the dispersion of the random numbers. For instance, higher parameter values result in less dispersion of the random values. When the parameter is close to one, the random values are not correlated.

On the other hand, the Gaussian and *t*-copula are elliptical copulas. In these cases, the correlation parameter ρ controls the dispersion of the random values. Values of ρ close to one, more correlated marginals. Within the elliptical copulas, the *t*-copula has two parameters; therefore, the *t*-copula offers another feature, the tail dependency. This additional parameter allows the *t*-copula to simulate values at the corners of the distribution space. This flexibility is given by the degrees of freedom v. For instance, fixing the correlation parameter and changing the degrees of freedom to higher values, in a *t*-copula density, results in a Gaussian copula. That said, *t*-copula is more flexible than Gaussian.

We selected the Gaussian copula in this investigation for two main reasons. First, elliptical copulas can easily model high dimensions, since the diagonal of the correlation matrix has the same dimension as the number of components considered. Archimedean copulas are practically implemented for only two components. Second, since we do not have a quantitative perception of the right value for the degree of freedom v in the *t*-copula and is certainly more costly from the computation point of view, we decided to use Gaussian over t-copula because we aim to assess if correlated wind values impact the delivery energy path and maintenance scheduling activities allocation, and for that, Gaussian is sufficient.

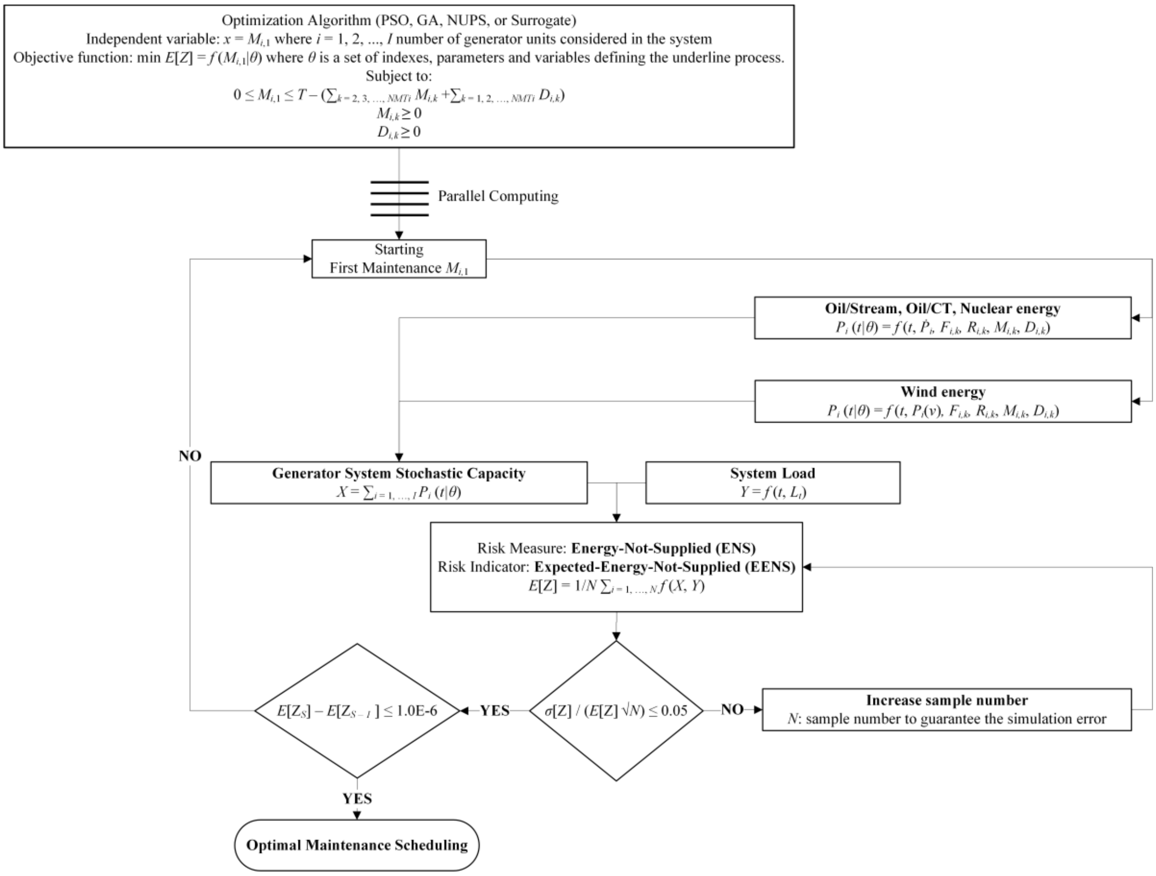

Figure 1. Flow diagram to solve the optimization problem of maintenance scheduling.

Previously, with (1), uncorrelated random numbers u_i were generated for each unit i considered in the system, to obtain the wind speed values v_i for each wind turbine. Now, we simulate a matrix with dimension $[I, T]$ of correlated marginals $U_{[0,1]}(\rho)$, where ρ is the correlation parameter controlling the dispersion of random values, I is the number of offshore wind turbines within the wind farm, and T is the simulation window in hourly resolution. Then, using the $U_{I,T}$, and the parametrized Weibull distribution, we obtain a matrix of $V_{I,T}$, which is the correlated wind speed simulations as shown in (2), and then, with the power characteristics function of the wind turbine, we translate the wind speed values into energy. For wind turbines, the variable $P_i(t|v)$ represents the wind power of the i-th wind turbine at the t-th time, as illustrated in Figure 1.

$$V_{I,T} = \delta\left[-\ln\left(U_{I,T}\right)\right]^{1/\beta} \quad (2)$$

At this point, we end the description of the modeling changes. The following modeling steps remain unchanged as presented in [3]. In Section 3, we present the parameterized scenario used to assess the impact of the modeling change introduced in this paper.

3 RESULTS AND DISCUSSION

In this section, we describe scenario parameterization, then we illustrate the experiment designed to measure the deviations in the EENS estimations when correlations in the wind speed are considered, and then we provide the solution for the system maintenance scheduling activities under highly correlated wind speed conditions using two heuristic optimization algorithms. The parameterization of each algorithm is also presented, as well as a comparison between them.

The base scenario described in [3] is partially used to validate the revised methodology. However, we recap key information here to highlight what is relevant for the analysis of this contribution. The IEEE Reliability Test System (IEEE-RTS) suggested by the Subcommittee on Applications of Probabilistic Methods provides the basis for the scenario and is particularly suitable for implementing maintenance planning solutions [15]. Tables 1 and 2 show the parameterization implemented in the scenario under study. The original IEEE-RTS has 32 generators and an overall capacity of 3405 MW. However, a modification is introduced in the scenario to integrate offshore wind farms. The wind turbine parameters assumed to make up the offshore wind farms modeled in this contribution are listed in Table 3. This modified scenario replaced three 100 MW Oil/Stream generator units with offshore wind farms. In particular, three farms with 50 wind turbines of 2 MW, making a total of 300 MW, which is the same capacity as the replaced generator units.

In this modified scenario, even if the replacement total nominal capacity is the same (300 MW), there is a difference in the primary source of energy. Usually, in the case of Oil/Stream generators, the primary source of energy is always available. In the case of wind farms, the primary source of energy is the wind and it is subject to changes and variability. Therefore, the contribution of wind energy will never be 100%; in other words, even if we have 300 MW installed, in practice, the potential energy to be used will certainly be less. Selecting the same nominal capacity points out this difference.

In this modified scenario, as we introduced three offshore wind farms, the number of individual generator units increased from 32 to 179. Figure 2 shows the connection schema of the wind farms with the Power System, which is the connection to the grid. Essentially, three wind farms are connected in parallel and located in different locations, and the wind characteristics are also related to the location.

Since we use a Monte Carlo method to estimate the EENS, we assume that β = 5% (error criterion) and T = 8760 hours (simulation time window).

Table 1. Parameterization of Scenario (A)

No. Units	Unit Capacity (MW) $\dot{P}_i$	MTTF (hours)	MTTR (hours)
5	12	2940	60
4	20	450	50
6	50	1980	20
4	76	1960	40
4	155	960	40
3	197	950	50
1	350	1150	100
2	400	1100	150
150	2	3650	55

Table 2. Parameterization of Scenario (B)

No. Units	$M_{i,k}$ (hours/year)	Maintenance (hours/year) $D_{i,k}$	N_{MTi}
5	672	168, 168	2
4	672	168, 168	2
6	672	168, 168	2
4	672, 672	168, 168, 168	3
4	672, 672, 672	168, 168, 168, 168	4
3	672, 672, 672	168, 168, 168, 168	4
1	672, 672, 672, 672	168, 168, 168, 168, 168	5
2	672, 672, 672, 672, 672	168, 168, 168, 168, 168, 168	6
150	672, 672, 672, 672, 672	168, 168, 168, 168, 168, 168	6

Table 3. Wind speed and wind turbine parameters

Parameter	Values Considered
μ_{sw}	19.52 km/h
σ_{sw}	10.99 km/h
P_r	2 MW
v_{ci}	15 km/h
v_r	36 km/h
v_{co}	80 km/h

Once the parameterization is known, we assess the deviations in EENS when correlations in the wind speed are considered within each wind farm. The differences are clearly illustrated in Figures 3-6 and discussed in this section.

Figure 3 shows the wind farm 1 delivery energy in the first five days when the wind simulation is assumed to be uncorrelated. As we can see, even if the total capacity of wind farm 1 is 100 MW, there is no peak value above 35 MW in the simulation. On the other hand, Figure 4 shows the same wind farm 1, but under the assumption that wind speed simulations are highly correlated. Certainly, the outcome of wind farm delivery is between these two extreme simulations (uncorrelated and highly correlated) in a real scenario, and the shape of how the energy is delivered changes drastically.

In the system analyzed, we consider three wind farms. Figure 5 shows the energy delivered in the first five days if uncorrelated wind simulations are assumed. As we can see, 300 MW of wind capacity only delivers a peak value slightly above 90 MW. On the other hand, Figure 6 shows the delivery energy when a highly correlated wind speed is assumed in each wind farm, but also assuming that each wind farm is in a different location, which means that there should be no correlation between wind farms. Again, the shape of the delivery energy changes, and we can see peak values reaching almost 250 MW.

Table 4. Variations in the correlation of wind speed.

Dev.	Wind Farm 1	Wind Farm 2	Wind Farm 3	EENS
6.23%	0.99	0.99	0.99	20,385
5.60%	0.90	0.90	0.90	20,265
4.93%	0.80	0.80	0.80	20,137
4.40%	0.70	0.70	0.70	20,035
2.79%	0.60	0.60	0.60	19,725
2.03%	0.50	0.50	0.50	19,579
1.73%	0.40	0.40	0.40	19,522
1.56%	0.30	0.30	0.30	19,490
1.18%	0.20	0.20	0.20	19,416
0.33%	0.10	0.10	0.10	19,253
0.00%	0.00	0.00	0.00	19,190

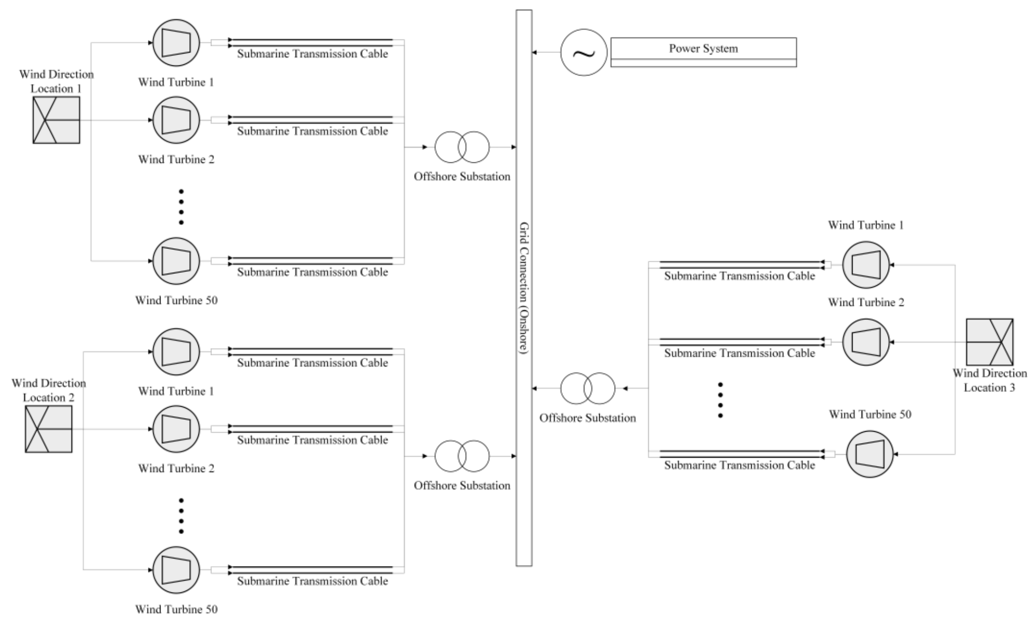

Figure 2. Power system and offshore wind farms connection schema.

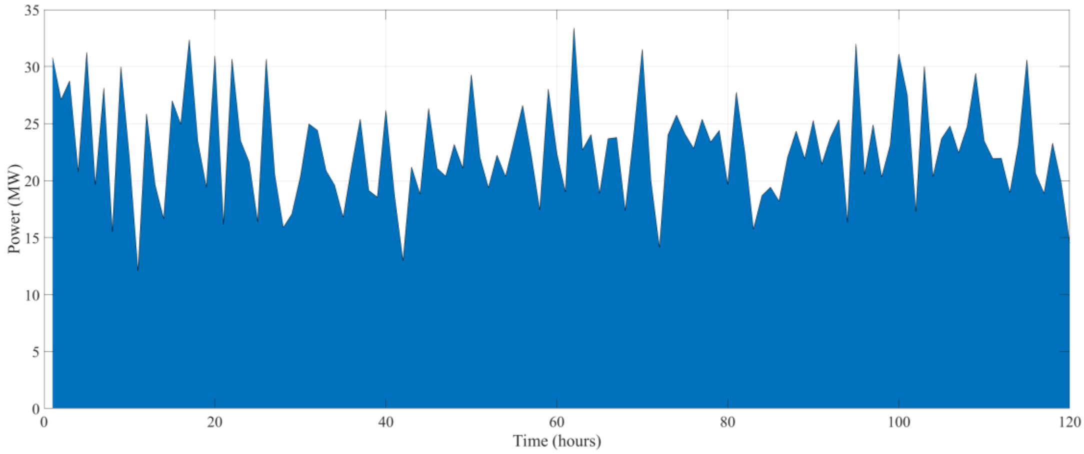

Figure 3. One wind farm simulated delivery energy with no-correlated wind speed.

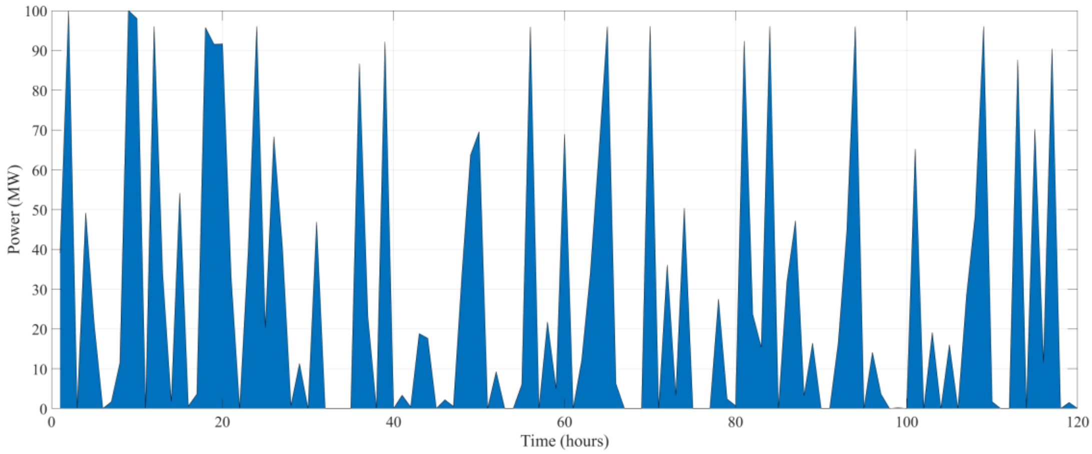

Figure 4. One wind farm simulated delivery energy with fully correlated wind speed.

Knowing that the shape of the delivery energy changes, we first quantify the holistic impact using the EENS indicator (MWh / year) and a predetermined maintenance scheduling activity solution for this case study, taken from [3]. Then we gradually introduce the correlations as described in Table 4.

As we can see in Table 4, deviations above 6% are observed in the EENS indicator. In fact, when an uncorrelated wind speed is assumed in the simulation, the dimension of the capacity of the system can be overestimated, as Figure 7 shows. In this experiment, we kept the random seeds unchanged to isolate the actual impact of the correlations. Additionally, Table 5 shows deviations slightly higher than 3% in the annual energy delivered by wind farms when correlations are introduced. This result confirms that assuming correlations in wind speed impacts not only the individual energy delivery of each wind farm, but also the overall behavior of the system, since the deviations in the EENS indicator are higher than the deviations of energy in the wind farms.

Table 5. Energy delivered (MWh/year)

Wind Farm	Uncorrelated	Correlated	Deviation
1	186,607	183,381	1.76%
2	185,665	190,449	-2.51%
3	185,814	191,879	-3.16%

Once presented with the impacts of the new assumption, we solve the maintenance scheduling problem under the new conditions, specifically, under a highly correlated assumption ($\rho = 0.99$). For this aim, we tested two heuristic optimization algorithms. In this paper, we use MATLAB [14] in the proposed implementation, and we use well-implemented MathWorks algorithms for the solution, specifically Particle Swarm Optimization (PSO) and Surrogate Optimization. Independent of the algorithm strategy, we assume that the optimization process ends when the difference between two consecutive evaluations in the objective function is less than 1.0E-06. Tables 6 and 7 show the maintenance scheduling activities solution for each algorithm, and Figures 8 and 9 show the convergence of the algorithms.

In the case of Surrogate, the algorithm required 8,950 evaluations in the objective function to achieve an EENS value of 20,798 MWh/year. The PSO required 26,000 evaluations (260 iterations and populations of 100 candidates) to achieve 17,306 MWh/year. Although Surrogate requires less execution time, the PSO can find a better solution. Since we face a nondeterministic polynomial time (NP) problem addressed with heuristics, algorithms are prone to finding a local minimum. Therefore, for this problem, PSO provides the best solution.

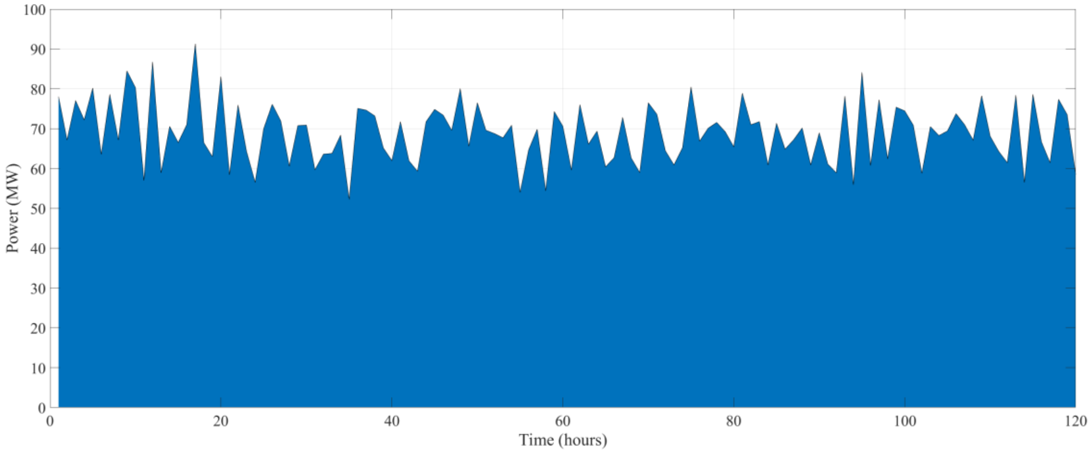

Figure 5. Three wind farms simulated delivery energy without correlated wind speed.

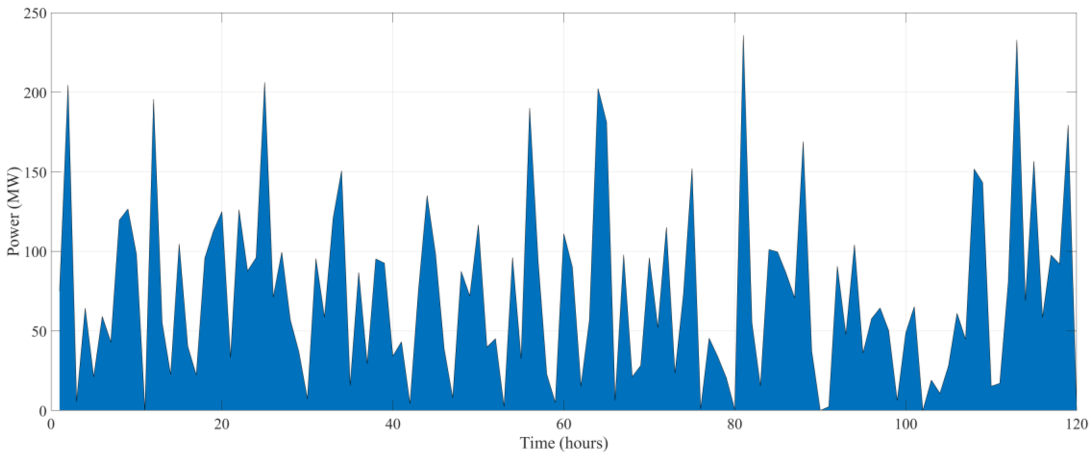

Figure 6. Three wind farms simulated the delivery energy with a fully correlated wind speed.

As we can see, the PSO adapted the solution to the new modeling conditions, since the EENS achieved = 17,306 MWh/year is 18% lower than the previous scheduling solution with the new modeling conditions, EENS = 20,385 MWh/year.

Figure 10 illustrates the system capacity versus system load under the new conditions, and Figure 11 shows the spatial distribution of the solution for maintenance scheduling activities.

Table 6. Maintenance scheduling solutions for offshore wind farms

Unit No.	Capacity	Start Maintenance PSO		Surrogate	
1	12	1727	'13-Mar-1900 23:00:00'	7053	'21-Oct-1900 21:00:00'
2	12	4007	'16-Jun-1900 23:00:00'	1392	'28-Feb-1900 00:00:00'
3	12	4674	'14-Jul-1900 18:00:00'	6344	'22-Sep-1900 08:00:00'
4	12	1117	'16-Feb-1900 13:00:00'	6296	'20-Sep-1900 08:00:00'
5	12	589	'25-Jan-1900 13:00:00'	0	'01-Jan-1900 00:00:00'
6	20	5562	'20-Aug-1900 18:00:00'	6214	'16-Sep-1900 22:00:00'
7	20	4999	'28-Jul-1900 07:00:00'	5406	'14-Aug-1900 06:00:00'
8	20	4548	'09-Jul-1900 12:00:00'	3954	'14-Jun-1900 18:00:00'
9	20	1190	'19-Feb-1900 14:00:00'	4970	'27-Jul-1900 02:00:00'
10	50	6091	'11-Sep-1900 19:00:00'	1549	'06-Mar-1900 13:00:00'
11	50	5958	'06-Sep-1900 06:00:00'	1287	'23-Feb-1900 15:00:00'
12	50	6600	'03-Oct-1900 00:00:00'	2496	'15-Apr-1900 00:00:00'
13	50	4432	'04-Jul-1900 16:00:00'	1436	'01-Mar-1900 20:00:00'
14	50	885	'06-Feb-1900 21:00:00'	5142	'03-Aug-1900 06:00:00'
15	50	5794	'30-Aug-1900 10:00:00'	4219	'25-Jun-1900 19:00:00'
16	76	614	'26-Jan-1900 14:00:00'	2980	'05-May-1900 04:00:00'
17	76	6216	'17-Sep-1900 00:00:00'	5656	'24-Aug-1900 16:00:00'
18	76	5531	'19-Aug-1900 11:00:00'	4924	'25-Jul-1900 04:00:00'
19	76	4648	'13-Jul-1900 16:00:00'	1667	'11-Mar-1900 11:00:00'
20	155	4295	'28-Jun-1900 23:00:00'	5039	'29-Jul-1900 23:00:00'
21	155	2340	'08-Apr-1900 12:00:00'	4697	'15-Jul-1900 17:00:00'
22	155	130	'06-Jan-1900 10:00:00'	63	'03-Jan-1900 15:00:00'
23	155	5575	'21-Aug-1900 07:00:00'	4574	'10-Jul-1900 14:00:00'
24	197	275	'12-Jan-1900 11:00:00'	5105	'01-Aug-1900 17:00:00'
25	197	3	'01-Jan-1900 03:00:00'	972	'10-Feb-1900 12:00:00'
26	197	4546	'09-Jul-1900 10:00:00'	4850	'22-Jul-1900 02:00:00'
27	350	1317	'24-Feb-1900 21:00:00'	530	'23-Jan-1900 02:00:00'
28	400	1840	'18-Mar-1900 16:00:00'	2749	'25-Apr-1900 13:00:00'
29	400	1642	'10-Mar-1900 10:00:00'	1689	'12-Mar-1900 09:00:00'
30	2	3880	'11-Jun-1900 16:00:00'	1294	'23-Feb-1900 22:00:00'
31	2	3589	'30-May-1900 13:00:00'	2115	'30-Mar-1900 03:00:00'
32	2	3085	'09-May-1900 13:00:00'	1531	'05-Mar-1900 19:00:00'
33	2	599	'25-Jan-1900 23:00:00'	736	'31-Jan-1900 16:00:00'
34	2	4388	'02-Jul-1900 20:00:00'	1519	'05-Mar-1900 07:00:00'
35	2	2122	'30-Mar-1900 10:00:00'	2420	'11-Apr-1900 20:00:00'
36	2	4389	'02-Jul-1900 21:00:00'	1800	'17-Mar-1900 00:00:00'
37	2	1902	'21-Mar-1900 06:00:00'	4141	'22-Jun-1900 13:00:00'
38	2	242	'11-Jan-1900 02:00:00'	1566	'07-Mar-1900 06:00:00'
39	2	3961	'15-Jun-1900 01:00:00'	1423	'01-Mar-1900 07:00:00'
40	2	1721	'13-Mar-1900 17:00:00'	3541	'28-May-1900 13:00:00'
41	2	1364	'26-Feb-1900 20:00:00'	2290	'06-Apr-1900 10:00:00'
42	2	3247	'16-May-1900 07:00:00'	61	'03-Jan-1900 13:00:00'
43	2	340	'15-Jan-1900 04:00:00'	2219	'03-Apr-1900 11:00:00'
44	2	7	'01-Jan-1900 07:00:00'	4118	'21-Jun-1900 14:00:00'
45	2	4378	'02-Jul-1900 10:00:00'	3994	'16-Jun-1900 10:00:00'
46	2	4182	'24-Jun-1900 06:00:00'	1593	'08-Mar-1900 09:00:00'
47	2	4278	'28-Jun-1900 06:00:00'	331	'14-Jan-1900 19:00:00'
48	2	3	'01-Jan-1900 03:00:00'	3441	'24-May-1900 09:00:00'
49	2	726	'31-Jan-1900 06:00:00'	1763	'15-Mar-1900 11:00:00'
50	2	228	'10-Jan-1900 12:00:00'	3167	'12-May-1900 23:00:00'
51	2	2241	'04-Apr-1900 09:00:00'	2153	'31-Mar-1900 17:00:00'
52	2	4064	'19-Jun-1900 08:00:00'	2353	'09-Apr-1900 01:00:00'

53	2	2583	'18-Apr-1900 15:00:00'	3018	'06-May-1900 18:00:00'
54	2	3732	'05-Jun-1900 12:00:00'	4	'01-Jan-1900 04:00:00'
55	2	2658	'21-Apr-1900 18:00:00'	3652	'02-Jun-1900 04:00:00'
56	2	4351	'01-Jul-1900 07:00:00'	3770	'07-Jun-1900 02:00:00'
57	2	2955	'04-May-1900 03:00:00'	3072	'09-May-1900 00:00:00'
58	2	83	'04-Jan-1900 11:00:00'	3164	'12-May-1900 20:00:00'
59	2	391	'17-Jan-1900 07:00:00'	3559	'29-May-1900 07:00:00'
60	2	930	'08-Feb-1900 18:00:00'	1816	'17-Mar-1900 16:00:00'
61	2	4364	'01-Jul-1900 20:00:00'	948	'09-Feb-1900 12:00:00'
62	2	3390	'22-May-1900 06:00:00'	574	'24-Jan-1900 22:00:00'
63	2	1600	'08-Mar-1900 16:00:00'	4341	'30-Jun-1900 21:00:00'
64	2	2213	'03-Apr-1900 05:00:00'	2561	'17-Apr-1900 17:00:00'
65	2	2253	'04-Apr-1900 21:00:00'	1010	'12-Feb-1900 02:00:00'
66	2	4	'01-Jan-1900 04:00:00'	678	'29-Jan-1900 06:00:00'
67	2	752	'01-Feb-1900 08:00:00'	579	'25-Jan-1900 03:00:00'
68	2	3008	'06-May-1900 08:00:00'	3060	'08-May-1900 12:00:00'
69	2	2232	'04-Apr-1900 00:00:00'	1287	'23-Feb-1900 15:00:00'
70	2	3665	'02-Jun-1900 17:00:00'	2890	'01-May-1900 10:00:00'
71	2	353	'15-Jan-1900 17:00:00'	322	'14-Jan-1900 10:00:00'
72	2	349	'15-Jan-1900 13:00:00'	291	'13-Jan-1900 03:00:00'
73	2	754	'01-Feb-1900 10:00:00'	1455	'02-Mar-1900 15:00:00'
74	2	3403	'22-May-1900 19:00:00'	3835	'09-Jun-1900 19:00:00'
75	2	4043	'18-Jun-1900 11:00:00'	2888	'01-May-1900 08:00:00'
76	2	1951	'23-Mar-1900 07:00:00'	997	'11-Feb-1900 13:00:00'
77	2	2325	'07-Apr-1900 21:00:00'	1056	'14-Feb-1900 00:00:00'
78	2	4085	'20-Jun-1900 05:00:00'	2241	'04-Apr-1900 09:00:00'
79	2	1663	'11-Mar-1900 07:00:00'	36	'02-Jan-1900 12:00:00'
80	2	2357	'09-Apr-1900 05:00:00'	1900	'21-Mar-1900 04:00:00'
81	2	601	'26-Jan-1900 01:00:00'	4392	'03-Jul-1900 00:00:00'
82	2	2627	'20-Apr-1900 11:00:00'	4327	'30-Jun-1900 07:00:00'
83	2	4379	'02-Jul-1900 11:00:00'	1035	'13-Feb-1900 03:00:00'
84	2	4364	'01-Jul-1900 20:00:00'	3722	'05-Jun-1900 02:00:00'
85	2	2004	'25-Mar-1900 12:00:00'	1002	'11-Feb-1900 18:00:00'
86	2	796	'03-Feb-1900 04:00:00'	4115	'21-Jun-1900 11:00:00'
87	2	1170	'18-Feb-1900 18:00:00'	1126	'16-Feb-1900 22:00:00'
88	2	3736	'05-Jun-1900 16:00:00'	3215	'14-May-1900 23:00:00'
89	2	1061	'14-Feb-1900 05:00:00'	2344	'08-Apr-1900 16:00:00'
90	2	4348	'01-Jul-1900 04:00:00'	1617	'09-Mar-1900 09:00:00'
91	2	4109	'21-Jun-1900 05:00:00'	159	'07-Jan-1900 15:00:00'
92	2	1545	'06-Mar-1900 09:00:00'	984	'11-Feb-1900 00:00:00'
93	2	60	'03-Jan-1900 12:00:00'	1933	'22-Mar-1900 13:00:00'
94	2	112	'05-Jan-1900 16:00:00'	1773	'15-Mar-1900 21:00:00'
95	2	4249	'27-Jun-1900 01:00:00'	2342	'08-Apr-1900 14:00:00'
96	2	1423	'01-Mar-1900 07:00:00'	3441	'24-May-1900 09:00:00'
97	2	126	'06-Jan-1900 06:00:00'	3616	'31-May-1900 16:00:00'
98	2	816	'04-Feb-1900 00:00:00'	2982	'05-May-1900 06:00:00'
99	2	233	'10-Jan-1900 17:00:00'	1694	'12-Mar-1900 14:00:00'
100	2	1229	'21-Feb-1900 05:00:00'	1659	'11-Mar-1900 03:00:00'
101	2	961	'10-Feb-1900 01:00:00'	632	'27-Jan-1900 08:00:00'
102	2	2851	'29-Apr-1900 19:00:00'	49	'03-Jan-1900 01:00:00'
103	2	4145	'22-Jun-1900 17:00:00'	3170	'13-May-1900 02:00:00'
104	2	207	'09-Jan-1900 15:00:00'	1227	'21-Feb-1900 03:00:00'
105	2	244	'11-Jan-1900 04:00:00'	1699	'12-Mar-1900 19:00:00'
106	2	1323	'25-Feb-1900 03:00:00'	20	'01-Jan-1900 20:00:00'
107	2	4174	'23-Jun-1900 22:00:00'	1779	'16-Mar-1900 03:00:00'
108	2	1683	'12-Mar-1900 03:00:00'	513	'22-Jan-1900 09:00:00'
109	2	4392	'03-Jul-1900 00:00:00'	3286	'17-May-1900 22:00:00'
110	2	565	'24-Jan-1900 13:00:00'	3653	'02-Jun-1900 05:00:00'
111	2	1783	'16-Mar-1900 07:00:00'	3676	'03-Jun-1900 04:00:00'
112	2	3555	'29-May-1900 03:00:00'	4040	'18-Jun-1900 08:00:00'
113	2	4309	'29-Jun-1900 13:00:00'	972	'10-Feb-1900 12:00:00'
114	2	2212	'03-Apr-1900 04:00:00'	2447	'12-Apr-1900 23:00:00'
115	2	4368	'02-Jul-1900 00:00:00'	2922	'02-May-1900 18:00:00'
116	2	2827	'28-Apr-1900 19:00:00'	0	'01-Jan-1900 00:00:00'
117	2	518	'22-Jan-1900 14:00:00'	3094	'09-May-1900 22:00:00'
118	2	4391	'02-Jul-1900 23:00:00'	2896	'01-May-1900 16:00:00'
119	2	3059	'08-May-1900 11:00:00'	1579	'07-Mar-1900 19:00:00'
120	2	2347	'08-Apr-1900 19:00:00'	4178	'24-Jun-1900 02:00:00'
121	2	873	'06-Feb-1900 09:00:00'	1476	'03-Mar-1900 12:00:00'
122	2	441	'19-Jan-1900 09:00:00'	25	'02-Jan-1900 01:00:00'
123	2	1876	'20-Mar-1900 04:00:00'	4356	'01-Jul-1900 12:00:00'
124	2	2066	'28-Mar-1900 02:00:00'	3851	'10-Jun-1900 11:00:00'
125	2	2572	'18-Apr-1900 04:00:00'	364	'16-Jan-1900 04:00:00'
126	2	2472	'14-Apr-1900 00:00:00'	2006	'25-Mar-1900 14:00:00'
127	2	4392	'03-Jul-1900 00:00:00'	3041	'07-May-1900 17:00:00'
128	2	1953	'23-Mar-1900 09:00:00'	3566	'29-May-1900 14:00:00'
129	2	967	'10-Feb-1900 07:00:00'	1514	'05-Mar-1900 02:00:00'
130	2	2021	'26-Mar-1900 05:00:00'	4216	'25-Jun-1900 16:00:00'
131	2	45	'02-Jan-1900 21:00:00'	2987	'05-May-1900 11:00:00'
132	2	1525	'05-Mar-1900 13:00:00'	2502	'15-Apr-1900 06:00:00'
133	2	1909	'21-Mar-1900 13:00:00'	757	'01-Feb-1900 13:00:00'
134	2	41	'02-Jan-1900 17:00:00'	3321	'19-May-1900 09:00:00'
135	2	4392	'03-Jul-1900 00:00:00'	1333	'25-Feb-1900 13:00:00'
136	2	3084	'09-May-1900 12:00:00'	4344	'01-Jul-1900 00:00:00'
137	2	570	'24-Jan-1900 18:00:00'	2328	'08-Apr-1900 00:00:00'
138	2	3065	'08-May-1900 17:00:00'	1103	'15-Feb-1900 23:00:00'
139	2	226	'10-Jan-1900 10:00:00'	0	'01-Jan-1900 00:00:00'
140	2	4388	'02-Jul-1900 20:00:00'	573	'24-Jan-1900 21:00:00'
141	2	1241	'21-Feb-1900 17:00:00'	4392	'03-Jul-1900 00:00:00'
142	2	4346	'01-Jul-1900 02:00:00'	1731	'14-Mar-1900 03:00:00'
143	2	345	'15-Jan-1900 09:00:00'	516	'22-Jan-1900 12:00:00'
144	2	3239	'15-May-1900 23:00:00'	3204	'14-May-1900 12:00:00'
145	2	2356	'09-Apr-1900 04:00:00'	4235	'26-Jun-1900 11:00:00'
146	2	418	'18-Jan-1900 10:00:00'	1320	'25-Feb-1900 00:00:00'
147	2	2376	'10-Apr-1900 00:00:00'	3596	'30-May-1900 20:00:00'
148	2	1	'01-Jan-1900 01:00:00'	4327	'30-Jun-1900 07:00:00'
149	2	3861	'10-Jun-1900 21:00:00'	29	'02-Jan-1900 05:00:00'
150	2	0	'01-Jan-1900 00:00:00'	3613	'31-May-1900 13:00:00'
151	2	2	'01-Jan-1900 02:00:00'	4354	'01-Jul-1900 10:00:00'
152	2	2288	'06-Apr-1900 08:00:00'	1621	'09-Mar-1900 13:00:00'
153	2	4183	'24-Jun-1900 07:00:00'	127	'06-Jan-1900 07:00:00'
154	2	304	'13-Jan-1900 16:00:00'	4097	'20-Jun-1900 17:00:00'
155	2	3052	'08-May-1900 04:00:00'	2257	'05-Apr-1900 01:00:00'
156	2	626	'27-Jan-1900 02:00:00'	0	'01-Jan-1900 00:00:00'
157	2	116	'05-Jan-1900 20:00:00'	1095	'15-Feb-1900 15:00:00'
158	2	524	'22-Jan-1900 20:00:00'	1380	'27-Feb-1900 12:00:00'
159	2	150	'07-Jan-1900 06:00:00'	2507	'15-Apr-1900 11:00:00'
160	2	1861	'19-Mar-1900 13:00:00'	3505	'27-May-1900 01:00:00'
161	2	1955	'23-Mar-1900 11:00:00'	416	'18-Jan-1900 08:00:00'
162	2	1868	'19-Mar-1900 20:00:00'	1881	'20-Mar-1900 09:00:00'
163	2	99	'05-Jan-1900 03:00:00'	1864	'19-Mar-1900 16:00:00'
164	2	4348	'01-Jul-1900 04:00:00'	2508	'15-Apr-1900 12:00:00'
165	2	2887	'01-May-1900 07:00:00'	3075	'09-May-1900 03:00:00'
166	2	4005	'16-Jun-1900 21:00:00'	72	'04-Jan-1900 00:00:00'
167	2	21	'01-Jan-1900 21:00:00'	2780	'26-Apr-1900 20:00:00'
168	2	495	'21-Jan-1900 15:00:00'	2387	'10-Apr-1900 11:00:00'
169	2	2936	'03-May-1900 08:00:00'	1972	'24-Mar-1900 04:00:00'
170	2	1171	'18-Feb-1900 19:00:00'	3668	'02-Jun-1900 20:00:00'
171	2	2984	'05-May-1900 08:00:00'	3336	'20-May-1900 00:00:00'
172	2	4377	'02-Jul-1900 09:00:00'	2398	'10-Apr-1900 22:00:00'
173	2	4386	'02-Jul-1900 18:00:00'	3395	'22-May-1900 11:00:00'
174	2	46	'02-Jan-1900 22:00:00'	1600	'08-Mar-1900 16:00:00'
175	2	3508	'27-May-1900 04:00:00'	4040	'18-Jun-1900 08:00:00'
176	2	120	'06-Jan-1900 00:00:00'	2137	'31-Mar-1900 01:00:00'
177	2	29	'02-Jan-1900 05:00:00'	2397	'10-Apr-1900 21:00:00'
178	2	3650	'02-Jun-1900 02:00:00'	3151	'12-May-1900 07:00:00'
179	2	746	'01-Feb-1900 02:00:00'	3975	'15-Jun-1900 15:00:00'

Table 7. Probabilistic impact assessment of maintenance scheduling solutions considering wind farms.

Risk Indicator EENS (MWh/year)	
PSO	Surrogate
17,306 [16,441; 18,171]	20,798 [19,758; 21,838]

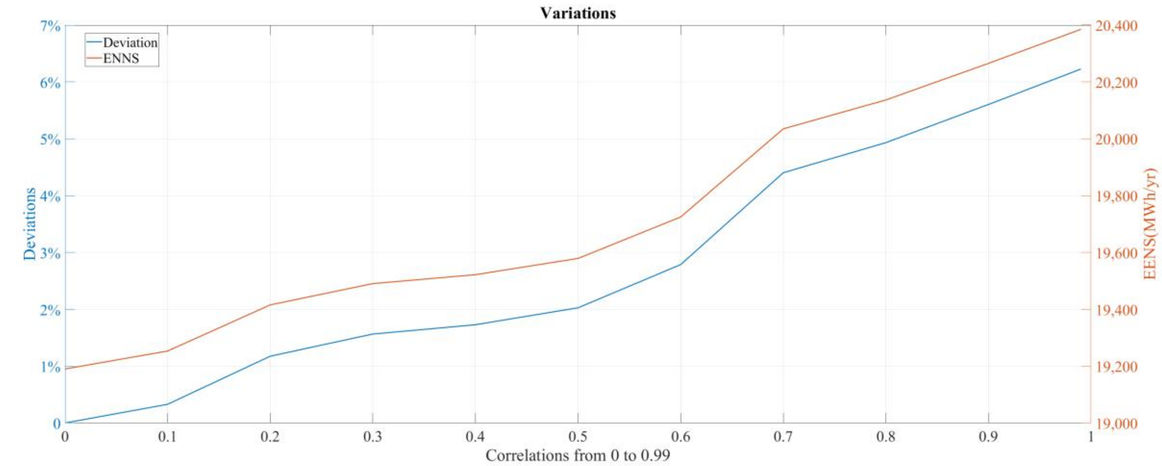

Figure 7. Variations due to correlated wind speed assumptions.

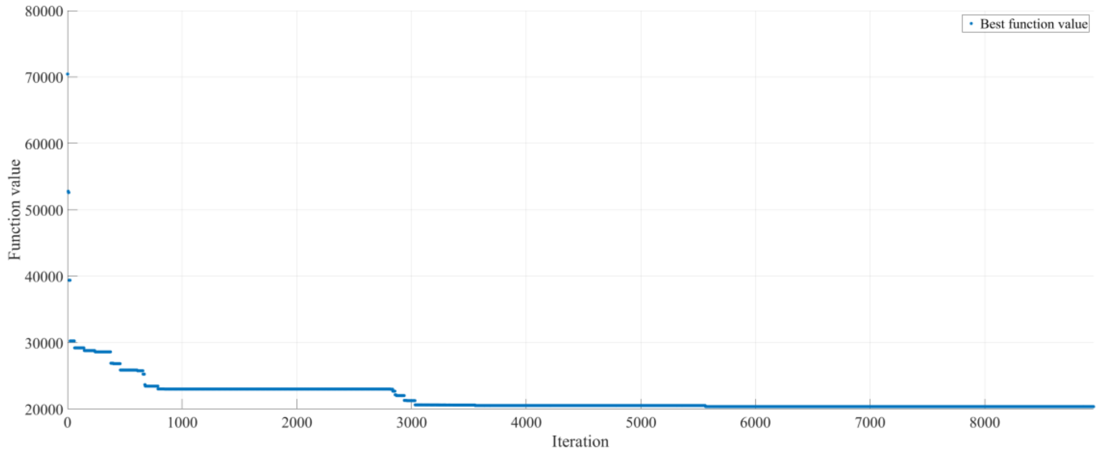

Figure 8. Convergence of the surrogate algorithm.

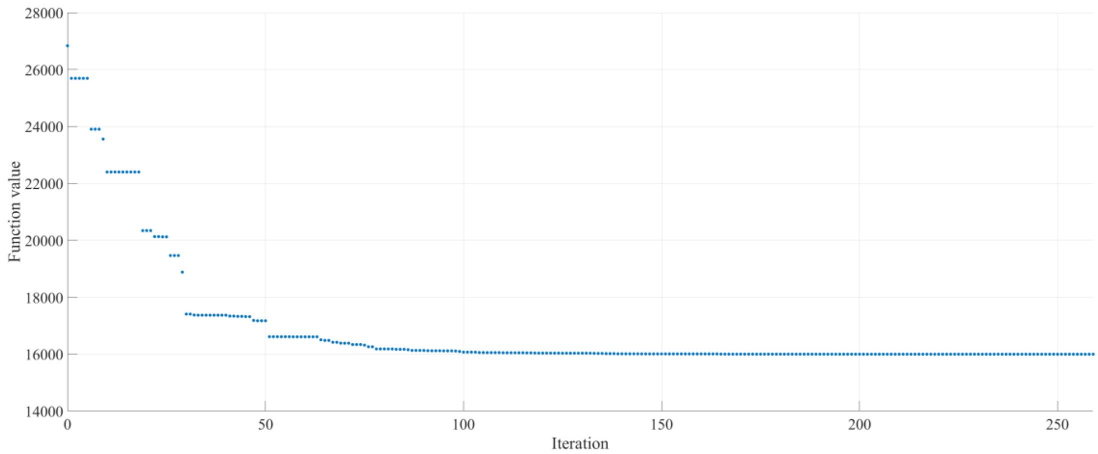

Figure 9. Convergence of the PSO algorithm.

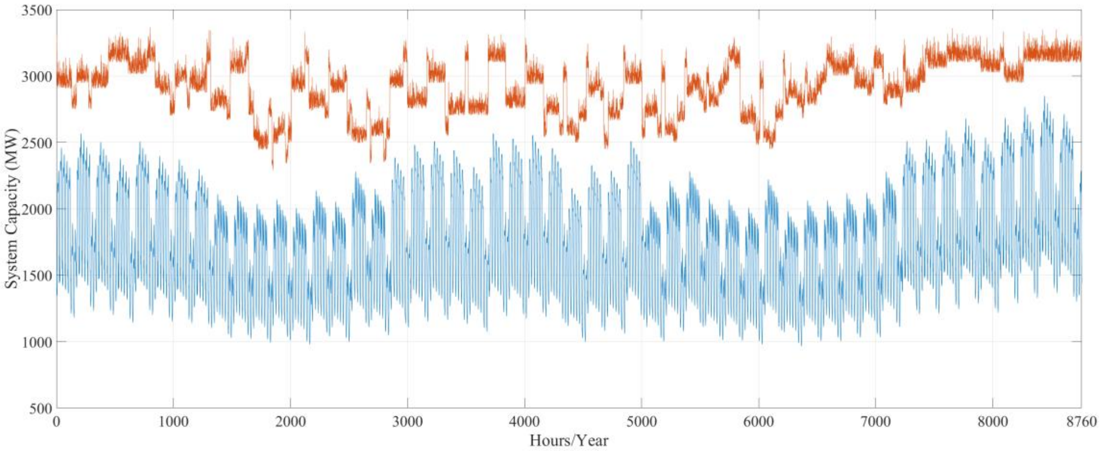

Figure 10. Generation capacity considering wind farms.

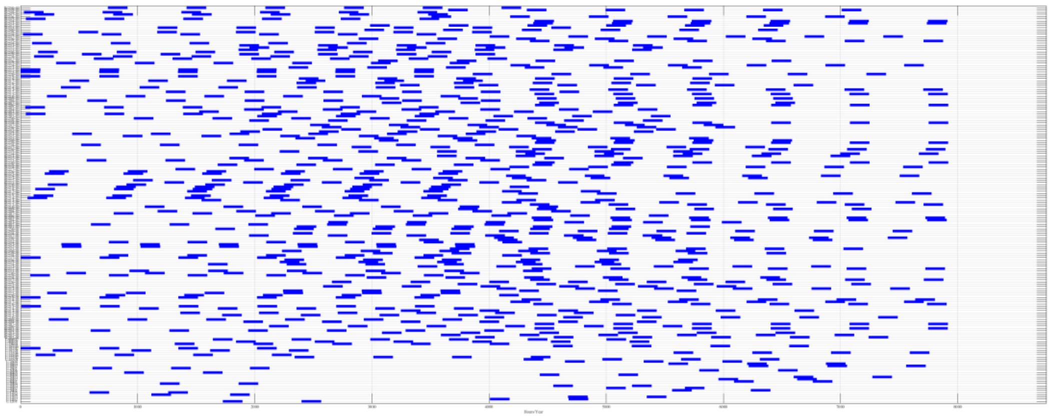

Figure 11. Maintenance scheduling schema.

4 CONCLUSIONS

This study introduced a revised methodology to optimize the coordination of maintenance activities in offshore wind farms within power systems. By integrating multivariate stochastic wind simulations into a maintenance scheduling framework, the proposed model captures the spatial and temporal dependencies inherent in offshore wind behavior, an aspect oversimplified or overlooked in previous results. Through extensive simulations based on IEEE-RTS and a revised methodology drawn from previous work, the results reveal that incorporating correlated wind speed significantly affects the estimation of Expected Energy Not Supplied (EENS). Specifically, deviations greater than 6% in EENS were observed under the same operational conditions when comparing uncorrelated and highly correlated wind scenarios. In addition, the new solution for maintenance scheduling activities is 18% lower than the previous solution under the new modeling conditions. These findings confirm that the wind speed correlation plays a critical role in system reliability and should be taken into account in realistic maintenance planning.

The use of copula-based modeling to simulate correlated wind speeds, combined with heuristic optimization algorithms (such as PSO and Surrogate models), allowed for a nuanced and effective scheduling of maintenance activities across dispersed units. Among the heuristics tested, PSO achieved the lowest EENS values, although further validation through sensitivity analysis is needed to establish its consistency across various scenarios. Certainly, this modeling change introduced in this paper exposes deviations (up to 6%) in the Expected Energy Not Supplied (EENS) indicator under the same operational conditions, purely due to changes in how wind speed correlations are handled. Such deviations have a direct impact on the allocation and timing of maintenance activities, indicating that overlooking wind correlation can lead to suboptimal or even misleading maintenance strategies.

By incorporating realistic wind behavior and spatial-temporal dependencies, the proposed methodology enables more robust, data-driven, and risk-aware planning of maintenance operations in offshore environments.

In the case of directions for further research, we plan to explore real operational data from actual offshore wind farms to validate the evidence of correlations in wind speed and introduce a dynamic and real-time scheduling approach by using real-time data assimilation and online adaptive optimization algorithms to dynamically adjust maintenance schedules.

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