Integrated Maintenance Decision Making Platform for Offshore Wind Farm with Optimal Vessel Fleet Size Support System

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ABSTRACT: The paper presents a model to coordinate the predictive-preventive maintenance process of Offshore Wind Farm (OWF) with optimal Vessel Fleet (VF) size support system. The model is presented as a bi-level problem. On the first level, the model coordinates the predictive-preventive maintenance of the OWF and the distributed Power System minimizing the risk of Expected Energy not Supply (EENS). The risk is estimated with a sequential Markov Chain Monte Carlo (MCMC) simulation model. On the second level the model determining the optimal fleet size of vessels to support maintenance activities at OWF.

1 INTRODUCTION

By the end of 2017, Europe leaded the global offshore energy market, with 83.9% share of the total installed capacity of 18.814 MW from 4.149 grid-connected wind turbines of 92 offshore wind farms in 11 countries. The UK has the largest amount representing 43.3%, followed by Germany. The total European offshore wind capacity is forecast at 25 GW by 2020 and 70 GW by 2030 (by then 7–11% of the EU's electricity demand is produced by offshore wind). Besides, the Chinese offshore wind energy market began in 2016 (14.9% market share), followed by Vietnam, Japan, South Korea and the US. With the growing engagement in the offshore wind industry worldwide, it is natural to investigate the operations and maintenance problems of the offshore wind farms. Given the difficulty in the techniques, availability, and accessibility due to the uncertain ocean wind environment, the maintenance costs for the offshore wind farms can form up to 25–30% of the energy cost and is typically estimated at five to ten times of the onshore maintenance cost. Once a failure occurs, a longer system downtime, and more loss in

revenue follow. Therefore, it is useful to study the maintenance problem of the offshore wind farms Zhong et al. (2019).

In recent literature we find several papers that study the maintenance problem of the offshore wind farms. Below we discuss some of the most accurate references in the solution of the problem posed:

Alcoba et al. (2017) propose a discrete optimization model that chooses an optimal fleet of vessel to support maintenance operations at Offshore Wind Farm. The model is presented as a bi-level problem. On the fist (tactical) level, decisions are made on the fleet composition for a certain time horizon. On the second (operational) level, the fleet is used to optimize the schedule of operations needed at the Offshore Wind Farm, given events of failures and weather conditions.

Zhong et al. (2018) proposed a non-linear multi-objective programming model including two newly defined objectives with thirteen families of constraints suitable for the preventive maintenance of offshore wind farms. In order to solve our model effectively,

the non-dominated sorting genetic algorithm II, especially for the multi-objective optimization is utilized and Pareto-optimal solutions of schedules can be obtained to offer adequate support to decision-makers. Finally, an example is given to illustrate the performances of the devised model and algorithm and explore the relationships of the two targets with the help of a contrast model.

Zhong et al. (2019) formulate a fuzzy multi-objective non-linear chance-constrained programming model with newly defined reliability and cost criteria and constraints to obtain satisfying schedules for wind turbine maintenance. To solve the optimization model, a 2-phase solution framework integrating the operational law for fuzzy arithmetic and the non-dominated sorting genetic algorithm II for multi-objective programming is developed. Pareto-optimal solutions of the schedules are obtained to form the trade-offs between the reliability maximization and cost minimization objectives. A numerical example is illustrated to validate the model.

Stalhane et al. (2016) determine the optimal fleet size and mix of vessels to support maintenance activities at offshore wind farms. A two-stage stochastic programming model is proposed where uncertainty in demand and weather conditions are considered. The model aims to consider the whole life span of an offshore wind farm and should at the same time remain solvable for realistically sized problem instances. The results from a computational study based on realistic data is provided.

Florian and Sorensen (2017) present how applications of risk and reliability-based methods for planning of Operation and Maintenance (O&M), can positively impact the cost of maintenance. The study focuses on maintenance of wind turbine blades, for which a fracture mechanics-based degradation model is set up. Based on this model, and the uncertain input in terms of cracking on the blades at the start of the lifetime, an initial reliability estimate is made. During the operation period, inspections are performed at regular time intervals, and the results are then used to update the reliability estimates using Bayesian networks. Based on the updated estimate, decisions on repairs are taken, thus potentially minimizing the maintenance effort while maintaining a target reliability level. To showcase the potential cost reduction, a study is made using a discrete event simulator. Two different preventive approaches are used. The first is a traditional time/condition-based strategy, where inspections are made with a fixed annual frequency and defects are repaired on detection. The second approach consists of risk-based inspection planning, using the methodology described in the first part of the paper, and the cost and availability savings relative to the previous strategy are underlined. A detailed description on the advantages of disadvantages of the risk strategy is given in the end of the paper.

Halvorsen-Weare et al. (2017) introduces a meta-heuristic solution method to determine cost-efficient vessel fleets to support maintenance tasks at offshore wind farms under uncertainty. It considers weather conditions and failures leading to corrective maintenance tasks as stochastic parameters and evaluates candidate solutions by a simulation program. The solution method has been incorporated in a decision support tool. Computational experiments, including comparison of results with an exact solution method, illustrate that the decision support tool can be used to provide near-optimal solutions within acceptable computational time.

1.1 *Contribution of this work*

Based on the previous references, in this paper we contribute with another approach to the maintenance problem solution of the offshore wind farms. In the first part of the paper (Level I) we analyze the relation between the Power System and the offshore wind farm and in the second part (Level II) we propose a new objective function based on workers demand to determinate the composition of the vessel fleet size support system to carry out the maintenance task in the offshore wind farms. On both levels we optimize non-linear stochastic functions.

2 MATERIALS AND METHODS

The bi-level optimization model formalized in this section to coordinate the Predictive-Preventive Maintenance Scheduling (PPMS) of the OWF with optimal vessel fleet size support system is structured in two steps. The first one consists in modeling the Power System and OWF with MCMC simulation model estimating the risk indicator EENS and based in this indicator and coordinate the PPMS, the second one in determining the optimal fleet size of vessels to support maintenance activities at OWF based on the workers demand and the fleet size capacity.

2.1 *Level I: Power System*

2.1.1 *Thermal unit modeling*

The operation of a thermal generating unit is continuous, eventually fails and is repairable. This random behavior can be described from Markov processes Yan et al. (2016). The Markov process allows modeling two stages: available and unavailable. For this case, transition rates are defined between the two states in which the generator can be. If the probability function of the transition rates from one state to another is exponential, they are denoted as λ (failure rate) and μ (repair rate) of the generator. Figure 1 shows a Markov process with two states: available and unavailable, and its transition rates λ and μ. For the two-state system represented in Figure 1, the system of differential equations with initial conditions $P_0(t) + P_1(t) = 1$, $P_0(0) = 1$ and $P_1(0) = 0$, that models the Markov process is shown in (1).
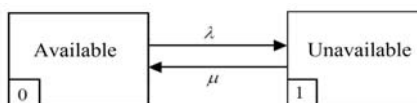

Figure 1. Two-state model for a generating unit.

$$\frac{dP_0}{dt} = -\lambda P_0(t) + \mu P_1(t)$$

$$\frac{dP_1}{dt} = -\mu P_1(t) + \lambda P_0(t)$$

(1)

The stationary solution of the differential equations system is denoted as availability A and unavailability U of a thermal generating unit. The parameter used to evaluate the static capacity of a thermal generating unit is the unavailability (2), also known as the Forced Outage Rate (*FOR*).

$$FOR = U = \frac{\lambda}{\lambda + \mu} = \frac{r}{m + r}$$

(2)

where the Mean Time to Failure (MTTF) is equal to $1/\lambda$, and the Mean Time to Repair (MTTR) is equal to $1/\mu$.

The MTTF and MTTR parameters are valid only if the random variables follow an exponential distribution. If the random behavior of Time to Failure (TTF) and Repair Times (TTR) is known, its average value can be obtained and consequently the *FOR* for each unit.

The generating units in the Power System are represented by a two-state model or a multi-state model. In the two-state model, the generating unit is considered fully available or totally unavailable to generate electricity (see Figure 1) and the two-state model is used to represent the generators that operate as base load. However, in the Power Systems there are peak load units or intermittent operating units. The functional characteristic that distinguish them is that they are turned on and off frequently. It is necessary to consider this behavior in the generating units' model. The Sub-Committee on Application of Probabilistic Methods of the IEEE proposed a four-state model Billinton and Huang (2006) for these generating units. This model is shown in Figure 2, where T is the average reserve shutdown time between periods of need, D is the average in-service time per occasion of demand and Ps is the probability of starting failure.
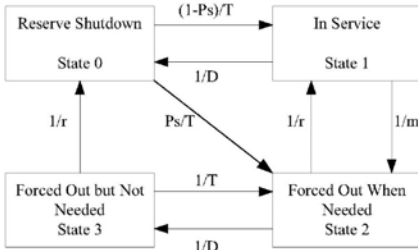

Figure 2. Four-state model for planning studies.

The four-state model, like the two-state model, is represented as a Markov process. The time-dependent solution of the differential equations system shown in (3) allows knowing the probabilities of each state. For the system of differential equations (3), the initial conditions are $P_0(t) + P_1(t) + P_2(t) + P_3(t) = 1$, $P_0(0) = 0$, $P_1(0) = 1$, $P_2(0) = 0$ and $P_3(0) = 0$.

$$\frac{dP_0(t)}{dt} = -\left(\frac{1-Ps}{T} + \frac{Ps}{T}\right)P_0(t) + \frac{1}{D}P_1(t) + \frac{1}{r}P_3(t)$$

$$\frac{dP_1(t)}{dt} = -\left(\frac{1}{D} + \frac{1}{r}\right)P_1(t) + \frac{1-Ps}{T}P_0(t) + \frac{1}{m}P_2(t)$$

$$\frac{dP_2(t)}{dt} = -\left(\frac{1}{m} + \frac{1}{D}\right)P_2(t) + \frac{Ps}{T}P_0(t) + \frac{1}{r}P_1(t) + \frac{1}{T}P_3(t)$$

$$\frac{dP_3(t)}{dt} = -\left(\frac{1}{r} + \frac{1}{T}\right)P_3(t) + \frac{1}{D}P_2(t)$$

(3)

when the probabilities associated with each state are known, the Utilization Forced Outage Probability (UFOP) is the probability of a thermal generating unit not being available when needed (4); therefore, the four-state model is reduced to a two-state model.

$$UFOR = \frac{P_2}{P_1 + P_2}$$

(4)

The stochastic capacity $U_i(t)$ at the time instant t of a thermal generating unit i is determined by the $MTTF_i$, $MTTR_i$ and C_i. The parameters $MTTF_i$, $MTTR_i$ and C_i allow to simulate with (5) the behavior of $U_i(t)$ generating k independent random numbers, assuming that they follow an exponential probability distribution with parameter $\lambda_i = 1/MTTF_i$ and $\mu_i = 1/MTTR_i$, which we will denote in this investigation as $TTF_{i,k} \sim E(\lambda_i)$ and $TTR_{i,k} \sim E(\mu_i)$.

On the other hand, one of the factors that affects the Power System capacity, is not stochastic and is not considered a random phenomenon, it is maintenance process of the generating units. Maintenance process is contemplated within the Power System strategies because it guarantees planned work time for the generating units. Maintenance is the activity designed to prevent failures in the production process and in this way reduce the risks of unexpected stops due to system failures. In the case of preventive maintenance, it is the planned activity in the vulnerable points at the most opportune moment, destined to avoid failures in the system. It is carried out under normal conditions, that is, when the productive process works correctly. In a Power System, to perform some preventive maintenance tasks it is necessary that the generating units does not work, and this causes loss of capacity in the Power System to supply the load. Due to this reason, it is advisable that this maintenance process be carried out at the time of the year where the least load exists, so that equilibrium and adequate flow are guaranteed in the Power System. To consider this effect, in this work the parameters $TTM_{i,k}$ and $TDM_{i,k}$ of the generating unit i are introduced and the equation (5).

The model proposed to simulate conventional generating units is defined below:

$$U_i(t) = \begin{cases} C_i & \text{if} \quad t < S_{1_{i,m}} + S_{2_{i,m-1}} \\ 0 & \text{if} \quad S_{1_{i,m}} + S_{2_{i,m-1}} \le t < S_{1_{i,m}} + S_{2_{i,m}} \\ 0 & \text{if} \quad A_{1_{i,n}} + A_{2_{i,n-1}} \le t < A_{1_{i,n}} + A_{2_{i,n}} \end{cases}$$

(5)

where: $i = 1, 2, \ldots, N_G$; $S_{1_{i,m}} = \sum_{k=1}^{m} TTF_{i,k}$ for $m = 2, 3, \ldots,$ MN_i; $S_{2_{i,m}} = \sum_{k=1}^{m} TTR_{i,k}$ for $m = 2, 3, \ldots, MN_i$; $A_{1_{i,n}} = \sum_{k=1}^{n} TTM_{i,k}$ for $n = 2, 3, \ldots, NK_i$; $A_{2_{i,n}} = \sum_{k=1}^{n} TDM_{i,k}$ for $n = 2, 3, \ldots, NK_i$.

2.1.2 *OWF modeling*

The two-state model is used to simulate the stochastic of faults and repairs in offshore wind turbines. The stochastic generation capacity $PWT(t)$ of an OWF at the moment of time t is determined by $MTTF_i$, $MTTR_i$ and $P_i(t)$ of each offshore wind turbine i. The difference between thermal and offshore wind turbine generating units, in this case, is that the power $P_i(t)$ depends on the wind SW_t. In the proposed model we use Weibull simulation approaches for the wind speed [Atwa et al. (2011)], so Weibull model generates random values from the density function adjusted with historical values. In the case of the power delivered by each offshore wind turbine we use the non-linear relationship between wind speed and wind turbine power given by Karki et al. (2012).

The wind speed is simulated with the Weibull model [Atwa et al. (2011)] estimating approximately the shape and scale parameters of the probability distribution density function with μ_{sw} and σ_{sw}. The Weibull probability distribution function for wind speed v is denoted as $f(v)$, β and δ are the shape and scale parameters of the distribution function respectively.

$$f(v) = \frac{\beta}{\delta}\left(\frac{v}{\delta}\right)^{\beta-1} e^{\left[-\left(\frac{v}{\delta}\right)^{\beta}\right]} \tag{6}$$

The parameters β and δ are obtained with the following expressions:

$$\beta = \left(\frac{\sigma_{sw}}{\mu_{sw}}\right)^{-1.086} \tag{7}$$

$$\delta = \frac{\mu_{sw}}{\Gamma(1+1/\beta)} \tag{8}$$

The inverse of cumulative probability distribution function (9) allows us to simulate the wind speed generating u uniformly distributed random numbers [0, 1] as shown in (10).

$$F(v) = 1 - e^{\left[-\left(\frac{v}{\delta}\right)^{\beta}\right]} \tag{9}$$

$$SW_t = v = -\delta \ln(1-u)^{1/\beta} = -\delta \ln(u)^{1/\beta} \tag{10}$$

The power delivered by each wind turbine is estimated with the function (11). The non-linear relationship between wind speed and wind turbine power is given by,

$$P(t) = \begin{cases} 0 & \text{if} \quad 0 \le SW_t < V_{ci} \\ (A + B \times (SW_t) + C \times (SW_t)^2) \times P_r & \text{if} \quad V_{ci} \le SW_t < V_r \\ P_r & \text{if} \quad V_r \le SW_t < V_{co} \\ 0 & \text{if} \quad SW_t \ge V_{co} \end{cases} \tag{11}$$

where P_r, V_{ci}, V_r and V_{co} are nominal output power, wind speed necessary for start-up, wind speed corresponding to the nominal power of the wind turbine and cutting wind speed per wind turbine safety reasons respectively Karki et al. (2012).

The constants A, B, and C depend on V_{ci}, V_r and V_{co} as shown in (12) Karki et al. (2012).

$$A = \frac{1}{(V_{ci}-V_r)^2}\left\{V_{ci}(V_{ci}+V_r) - 4V_{ci}V_r\left[\frac{V_{ci}+V_r}{2V_r}\right]^3\right\}$$

$$B = \frac{1}{(V_{ci}-V_r)^2}\left\{4(V_{ci}+V_r)\left[\frac{V_{ci}+V_r}{2V_r}\right]^3 - (3V_{ci}+V_r)\right\} \tag{12}$$

$$C = \frac{1}{(V_{ci}-V_r)^2}\left\{2 - 4\left[\frac{V_{ci}+V_r}{2V_r}\right]^3\right\}$$

The stochastic behavior of failures and repairs, and the PPMS is incorporated in $PE_i(t)$, modifying a parameter of (5), as shown in (13).

$$PE_i(t) = \begin{cases} P_i(t) & \text{if} \quad t < S_{1_{i,m}} + S_{2_{i,m-1}} \\ 0 & \text{if} \quad S_{1_{i,m}} + S_{2_{i,m-1}} \le t < S_{1_{i,m}} + S_{2_{i,m}} \\ 0 & \text{if} \quad A_{1_{i,n}} + A_{2_{i,n-1}} \le t < A_{1_{i,n}} + A_{2_{i,n}} \end{cases} \tag{13}$$

The power of the OWF is defined below as:

$$PWT(t) = \sum_{i=1}^{NA} PE_i(t) \tag{14}$$

where $i = 1, 2, \ldots, NA$.

2.1.3 *Load curve modeling:*

The load curve model is usually represented by the Daily Peak Load Variation Curve (DPLVC) or the Hourly Load Duration Curve (LDC) Billinton and Allan (1996). We used LDC because integrates the load curve chronological behavior. In the medium- and long-term planning studies, it is necessary to know the expected growth of the electrical demand of the Power System. The more widely used models of electrical demand forecast are the chronological series. These models forecast electricity demand based on historical behavior. ARIMA models (Auto Regressive, Integrated, Moving Average) are general models of time series Aminia et al. (2016). The general model is complex, but the models usually used are cases simpler. In this paper, an MA model is used, assuming for the study a 5% electrical demand growth and an uncertainty around the seasonal average of 10%, being expressed in (15) as:

$$D(t) = 1,05 \cdot \mu_t + 0,10 \cdot \alpha_t \tag{15}$$

where $D(t)$ is the estimated electrical demand at time t, μ_t is the average electrical demand of the last ten years at time t, $\alpha_t \sim N(0, \sigma_t^2)$ is a white noise process and σ_t is the standard deviation with respect to the average electrical demand of the last ten years at time t.

2.1.4 *Risk indicator modeling*

The risk function denoted as $R(s)$ can be generated with the sum $X + Y$ of the random, independent and non-negative variables X and Y.

The product of $R(s) = P(s) \, Q(s)$ is defined with the generating function $P(s) = \sum_{j=0}^{\infty} p_j s^j$ of X and the generating function $Q(s) = \sum_{j=0}^{\infty} q_j s^j$ of Y.

Consequently, the generating function of $R(s)$ is defined by the convolution formula (16).

$$r_k = \sum_{j=1}^{k} p_j q_{k-j} \tag{16}$$

If $R(s)$ is a random, independent and not negative variable, the arithmetic mean $(R_1 + R_2 + \ldots + R_n)/n$ of a random sample $R_1, R_2, \ldots R_n$ of the variable $R(s)$ is approximately equal to the expected value $E[R(s)]$, for large values of n.

In this investigation, X defined in equation (17) is probability distribution function of the thermal generating units stochastic capacity of the Power System, and Y defined in equation (18) is probability distribution function of the load curve incorporating the power delivered by the offshore wind farm as a negative demand:

$$X = \sum_{i=1}^{NG} U_i(t) \tag{17}$$

$$Y = D(t) - \sum_{i=1}^{NP} PWT_i(t) \tag{18}$$

where NP is the number of offshore wind farms considered in the installed capacity of the system.

The risk function is denoted in this investigation as R. This function is the convolution product of equations (17) and (18) defined in equation (19):

$$R = \begin{cases} \sum_{t=1}^{T} Y_t - X_t & \text{if} \quad X_t < Y_t \\ 0 & \text{if} \quad X_t \geq Y_t \end{cases} \tag{19}$$

The risk function expected value $E[R]$ is usually defined in the literature as Expected Energy Not Supplied (EENS), when the generating units capacities and the Power System electrical demand are expressed in megawatts and $t = 1, 2, \ldots, T$, considers the 8 760 hours of the year. In this work, to estimate $E[R]$ the Monte Carlo simulation method is used.

2.1.5 Optimization model

The proposed model objective is to minimize the expected value of the convolution function, between the probability distribution function of the thermal generating units stochastic capacity of the Power System, and the probability distribution function of the load curve incorporating the power delivered by the offshore wind farm as a negative demand. The model is defined below:

$$\min E[R]$$
subject to: $\tag{20}$
$$0 < TTM_{i,k} < 8760 - TDM_{i,k}$$

The stochastic non-linear optimization model proposed for the PPMS problem solution of the Power System presents only continuous variables $x = TTM_{i,k}$ and is defined in the model constraint intervals. The independent variable of the objective function to be optimized $x = x_1, x_2, \ldots, x_{NKi}$ depends on the quantity of preventive maintenance NK_i to be coordinated for each generating unit i. The optimization variables are only the start times for the first maintenance of each unit $TTM_{i,1}$. Once $TTM_{i,1}$ is established, the remaining $TTM_{i,k}$ are calculated adding the corresponding maintenance intervals, which are invariable.

2.2 Level II: Vessel Fleet Size Support System

2.2.1 Workers demand

The workers demand necessary to carry out the maintenance tasks in the OWF depends of how many wind turbines had PPMS at the same time. In this paper we use an empirical function to determinate the workers demand according to PPMS proposed for the Power System in the Level I problem.

The model proposed to determinate the workers demand WD_t is defined below:

$$WD_t = \begin{cases} WN_{1,t} & \text{if} \quad \sum_{i=1}^{N_{WT}} x_{i,t} = 1 \\ WN_{2,t} & \text{if} \quad \sum_{i=1}^{N_{WT}} x_{i,t} = 2 \\ \vdots & \vdots \\ WN_{N_{WT},t} & \text{if} \quad \sum_{i=1}^{N_{WT}} x_{i,t} = N_{WT} \end{cases} \quad \text{for} \quad t = 1, 2, \ldots, N_H \tag{21}$$

where WN_i workers number necessary to carry out the maintenance tasks in the offshore wind farm, N_{WT} number of offshore wind turbines, N_H number of hours in the year, $x_{i,t} \in [0, 1]$ is a binary variable, so is equal to 1 when the offshore wind turbine i have a maintenance tasks at instant of time t, and 0 otherwise.

2.3 Workers capacity

On another hands, the workers capacity depends of the vessel fleet size. It's typically found vessels and bases, each one has different capacity and the selection depends on maintenance tasks and necessary workers Alcoba et al., 2017; but we can define a general model as shown below:

$$WD_t = \left\{ WC = \sum_{i=1}^{N_V} x_{i,t} VC_{i,t} + \sum_{i=1}^{N_B} x_{i,t} BC_{i,t} \quad \text{for} \quad t = 1, 2, \ldots, N_H \right. \tag{22}$$

where WC workers number capacity to carry out the maintenance tasks in the offshore wind farm, N_V number of vessels, N_B number of bases, N_H number of hours in the year, $VC_{i,t}$ workers number capacity in the vessel i at instant of time t, $BC_{i,t}$ workers number capacity in the base i at instant of time t and $x_{i,t} \in [0, 1]$ is a binary vector with the array $x_1, x_2, \ldots, x_{NV}, x_{NV+1}, x_{NV+2}, \ldots, x_{NV+NB}$, so is equal to 1 when the vessel or

base i is necessary at instant of time t, and 0 otherwise.

2.3.1 *Optimization model*

The optimization model objective (23) is to determine the optimum vessel fleet size support system that guarantee to minimize the workers number needed to carry out the maintenance tasks in the offshore wind farm. The input is described by a set of decision-making combination x_1, x_2, …, x_{NV}, x_{NV+1}, x_{NV+2}, …, x_{NV+NB} defined in $x_{i,t} \in [0, 1]$. Penalties are introduced when the fleet is not able supplied the workers demand.

$$\min \sqrt{WC_t^2 - WD_t^2} \quad \text{for} \quad t = 1, 2, \ldots, N_H$$
$$\text{subject to:} \quad WC_t \geq WD_t \quad \forall t \tag{23}$$

3 RESULTS AND DISCUSSIONS

The Power System energy matrix analyzed is composed of diesel and fuel thermal generating units of the Table 1 and offshore wind farm of the Table 2. The OWF has a capacity of 2,75 MW and operates in base load throughout the year; therefore, two-state Markov model is used to simulate the wind farm stochastic capacity. However, in the case of fuel or diesel generating units, it is different.

The Power System analyzed has a maximum demand of 18 MW and a static capacity installed of 21 MW distributed in small capacity generating units. This characteristic condition the Power System operation. To satisfy the demand, fuel and diesel generating units are rotated according to the operating times, therefore, these units operate intermittently. For this reason, four-state Markov model is used for the simulation of diesel and fuel generating units. The offshore wind farm mathematical model needs other considerations for the simulation. We assume a wind mean μ_{sw} = 5.4 m/s and standard deviation σ_{sw} = 2.3, and with these values we calculate the shape and scale parameters of the Weibull probability distribution density function. The inverse of cumulative probability distribution function allows to simulate the wind speed behavior generating u uniformly distributed random numbers [0, 1]. The wind turbine used in this paper has a nominal power Pr of 275 kW, the cut-in speed wind V_{ci} is 4 m/s, the rated speed wind V_r is 10 m/s and the cut-out wind speed V_{co} is 25 m/s. For each wind turbine, the MTTF and MTTR data are shown in Table 2. In the investigation, load curve forecast of the system used is shown in Figure 3.

In the case of vessel fleet size support system, we assumed 10 workers demand for each wind turbine to carry out the maintenance tasks in time, and a fleet with 4 vessels with 8, 12, 16 and 30 workers capacity and 3 bases with 12, 24 and 36 workers capacity.

Table 1. Diesel and fuel units' indicators.

Unit	Capacity (MW)	MTTF	MTTR	D	T	Ps
1	1.88	150	100	5	20	0.0150
2	1.88	75	10	2	30	0.0090
3	1.88	190	60	2	15	0.0020
4	3.85	550	15	55	20	0.0225
5	3.85	850	25	65	15	0.0095
6	3.85	520	10	50	30	0.0085
7	3.85	720	15	35	15	0.0055

Note: The parameters MTTF, MTTR, D and T are expressed in hours.

Table 2. Offshore wind turbines indicators.

Wind turbine	Capacity (kW)	MTTF	MTTR
1	275	2500	485
2	275	1200	670
3	275	1550	380
4	275	1750	190
5	275	2500	990
6	275	550	350
7	275	2950	580
8	275	2450	450
9	275	1700	590
10	275	2580	200

Note: The parameters MTTF and MTTR are expressed in hours.

3.1 *Influence of predictive-preventive maintenance scheduling.*

In the real Power System analyzed, the PPMS of the generating units reduce considerably the system static capacity, increasing consequently the risk levels. This condition is critical in the system because forced output of a generating unit causes damages to the customers electric service. In this investigation, it is identified that the critical condition is associated with the generating units PPMS improper coordination. The paper proposes to coordinate the generating units PPMS with a nonlinear stochastic optimization model that aims to improve the Power System risk levels as much as possible (Platform concept). The paper shows how using the proposed model it is possible to coordinate the PPMS and improve the Power System risk levels. The influence of PPMS is considered in the estimates of risk indicators. Therefore, stochastic variables and PPMS are considered in the Power System static capacity simulation. The maintenance quantity and duration, and the moment when they are executed in the year, influences the Power System risk indicators. Conveniently, maintenance should be spaced in the year. This condition guarantees that the Power System static capacity is not greatly affected. The PPMS problem solution is complex because the search spaces dimension is large. Therefore, it is necessary to use computational optimization models to solve this problem. Figure 3 show a PPMS improper coordination because every maintenance task starts in the beginning of the year, and Figure 4 show the proposed results for the problem solution.
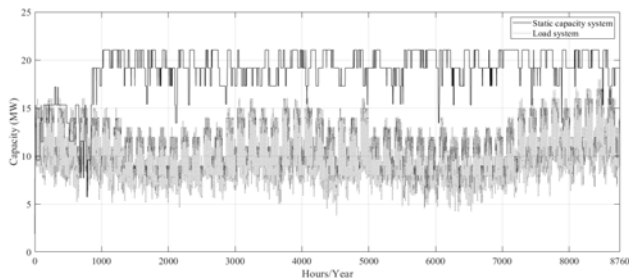
Figure 3. Static capacity with PPMS, failures and repairs time of all thermal generating units and the offshore wind farm in a simulate year.
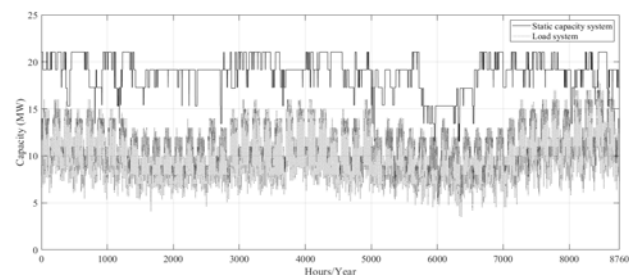

Figure 4. Static capacity with PPMS, failures and repairs time of all thermal generating units and the offshore wind farm in a simulate year (Problem solution).

3.2 *Optimal vessel fleet size support system*

Each maintenance task has several workers associate, in this paper we assuming that each wind turbine needs 10 workers to carry out in time the maintenance task coordinated in the first problem (Level I). The objective function proposal to determinate the best vessel fleet size based on workers demand is a no-linear stochastic function. Bellow we show in the Figure 5 the best vessel fleet size for a PPMS improper coordination, and Figure 6 show the best vessel fleet size to the problem solution.
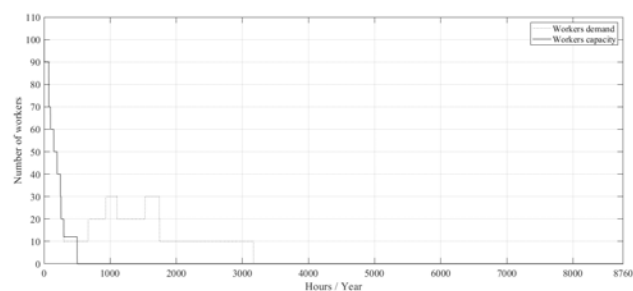
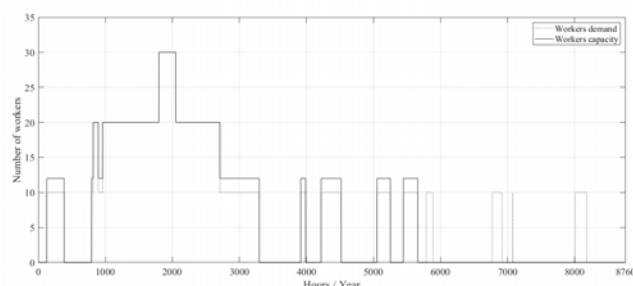

Figure 5. Best vessel fleet size.

Figure 6. Best vessel fleet size (Problem solution).

4 CONCLUSIONS

The work shows that the proposed platform concept based on risk assessment allows to schedule the PPMS of thermal generating units and offshore wind farm at the same time in the first level problem. We have presented a model to determine an optimal vessel fleet size for operation and maintenance activities at offshore wind farms in the second level problem. This paper has described a potential practical application for risk-based maintenance of offshore wind turbine.

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