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A PROBABILISTIC APPROACH TO INTRODUCE RISK MEASUREMENT INDICATORS TO AN OFFSHORE WIND PROJECT EVALUATION – IMPROVEMENT TO AN EXISTING TOOL ECUME

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Abstract

Offshore wind power is an emerging technology identified as a source of future growth by EDF Group, for which the number of wind farm projects will potentially increase in the future. Although there is greater potential for offshore wind generation, the investment to construct is more significant than onshore due with higher installation costs (essentially for foundations, electrical connections, towers and turbines). In addition to this, operation and maintenance needs more important access methods. In this context, a tool ECUME has been developed in recent years to support EDF Group in making its choices of investment, technologies and the development of operating and maintenance strategies for offshore wind turbines. The tool evaluates the total mean cost of operation of an offshore wind farm project, as early in the development process as its design phase, in order to help decision making on investment, technology selection, and life cycle logistics and maintenance strategies.

This paper proposes some improvements to ECUME in order to supply more accurate output indicators as a simple mean cost which is not sufficient to make investment decisions about a farm, a design or a maintenance strategy. These decisions in the offshore wind context are exposed to greater uncertainty of failure occurrence and inaccessibility. Risk measurement indicators better fitted to the decision context can take into account the uncertainties in the evaluation of risks. This allows EDF to understand the confidence that can be accorded to the mean value assessed and the range of values between which the indicator is distributed ; the risk that an investment is not profitable despite a positive mean Net Present Value, ... To provide these indicators, we introduce an event model (based on Monte-Carlo simulation) to model failure risk and HMM (Hidden Markov Model) to model the evolution of meteorological and marine parameters and evaluate inaccessibility risk.

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Keywords :Offshore, Wind Farm, Operation and Maintenance, Reliability

1. INTRODUCCION

1.1. *Offshore wind power generation in France*

Offshore wind power is an emerging generation technology which has been expanding rapidly for the last fifteen years. EU Member States have adopted a binding target of 20 % renewable energy by 2020. Therefore it is identified as a source of future growth by EDF Group, for which the number of wind farm projects will potentially increase in the future next years. In addition, the French government has recently published a call for tender for 3 GW of offshore wind power.

Offshore Wind offers great generation potential as it is estimated that between 20 GW and 40 GW of offshore wind energy capacity will be operating in the European Union by 2020 [1]. However the investment to construct is more significant than onshore due with higher installation and O&M costs. Indeed, offshore wind power needs significant focus on access means and the severe operational environment that affects the reliability of turbines (corrosion, impact of lightning, etc.). Moreover accessibility of sites can be impossible in severe weather.

In this context, choices of investment sites, technologies and O&M strategies for offshore wind turbines are crucial in order to ensure future project profitability.

1.2. *ECUME – needs of improvements*

To support EDF Group answering those questions, a tool (ECUME) has been developed in recent years. It evaluates the total mean cost of operation of an offshore wind farm project, as early as the design phase, in order to help decisions on investment and technology selection. It can also be used along the farm life cycle in order to support logistics and maintenance strategies.

In an industrial context, a simple mean cost is not sufficient to make investment decisions about a farm, a design or a maintenance strategy because, in the offshore wind power context, those decisions are exposed to the uncertainty of failures and of inaccessibility. Thus we propose in this paper some improvements to the tool in order to supply more accurate output indicators. Risk measurement indicators better fitted to the decision context can be listed as the confidence level for the mean value assessed and the range of values between which the indicator is distributed ; the risk that an investment is not profitable despite a positive mean Net Present Value, etc.

Figure 1 illustrates the benefits of these types of risk measurements. In this example, two strategies (S1 and S2) are compared on the basis of their NPV. If we only retain the mean NPV as a decision indicator, we would probably prefer S2 due to its higher mean NPV. But, looking at the distribution of the S1 and S2 NPV, we can also see that S2 can take negative values, and the result has lower confidence than S1.

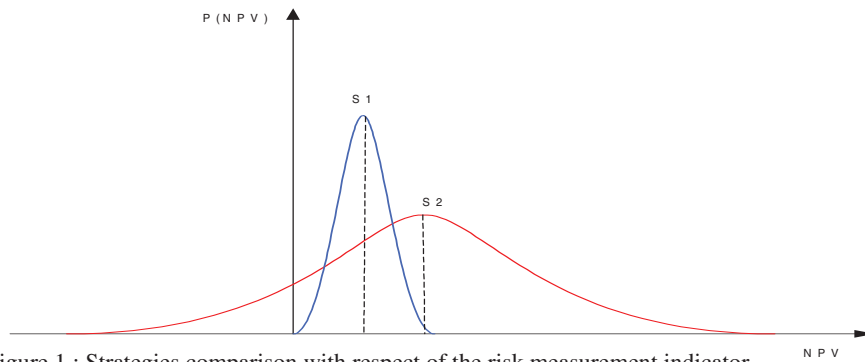


Figure 1 : Strategies comparison with respect of the risk measurement indicator

Nomenclature

EDF	Électricité de France
HMM	Hidden Markov Model
NPV	Net Present Value
O&M	Operation and Maintenance

2. ECUME BRIEF DESCRIPTION

ECUME is based on the ECN O&M cost model [2]. It evaluates the operation total mean cost of an offshore wind farm project. This cost is made of deterministic and probabilistic cash flows (Figure 2).

On the one hand, the deterministic cash flows are entered by the user. They consist of the capital costs of the wind farm and the operational costs (fixed costs, preventive maintenance costs for periodic visits, standard exchanges, monitoring for condition-based maintenance).

On the other hand, the probabilistic cash flows are costs due to corrective maintenance when failures occur and to condition-based maintenance when degradations are detected before failures. Each year, for each type of critical failure that can affect the turbine, those costs are proportional to the failure rate given by the user. Whatever is the type of maintenance (i.e. preventive, corrective or condition-based), costs include

- direct costs (labor, spare parts, transport, ...);
- indirect costs caused by turbine unavailability.

Unavailability is made up of the maintenance operation duration itself and of a waiting time before the maintenance operation can be performed. This waiting time is due to the potential inaccessibility of the site caused by access constraints. ECUME evaluates it for a given corrective maintenance operation as a mean value calculated by another internal tool, AMER. For a given weather window, which is a set of given constraints (wind speed limit, height of waves limit, etc.), AMER calculates the mean waiting time per season in order to have the correct meteorological window to perform the specific maintenance.

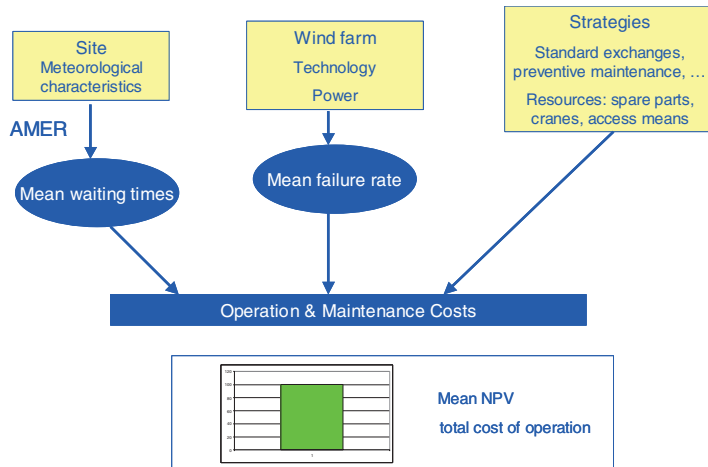


Figure 2 Actual version of ECUME

The indicators evaluated with ECUME are mean values which are not sufficient for our operational businesses decision making, therefore we propose to improve the tool.

3. ECUME IMPROVEMENTS

3.1. Introduction of the new event model

To provide more accurate output indicators, an event model based on Monte Carlo simulation is being prepared. It allows the generation of several scenarios of the offshore wind farm project all along its operational life cycle. Each scenario is a probable life of the offshore wind farm project (meteorological parameters evolution and maintenance dates) during which each maintenance activity induces :

- repair costs (i.e. labor, spare parts, access mean, ...) ;
- unavailability of the power supply that can be valued as a loss of electricity sales, until it has been restored.

Failure instances and meteorological parameters are intrinsically stochastic. Therefore, we have constructed two probabilistic models to simulate them:

- a failure model simulating failure instances according to a mix of Weibull distributions ;
- a meteorological and marine model simulating meteorological scenarios according to the past using a HMM (Hidden Markov Model) which is used to compute a waiting time for each failure instance.

Figure 3 summarizes the event model principles.

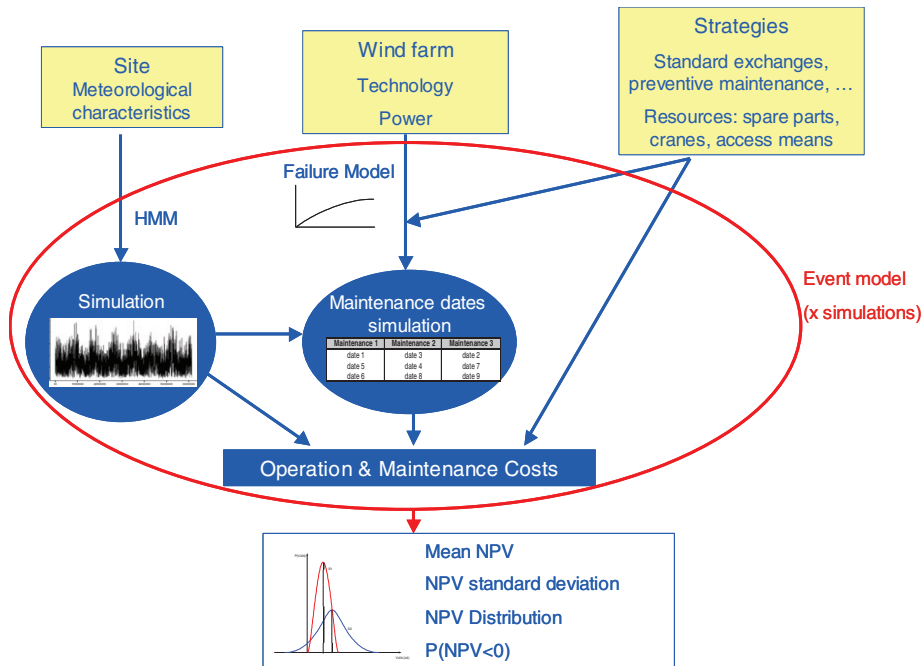


Figure 3 : Event model principles

The next two parts of this document describe the meteorological model and the failure model.

3.2. Meteorological and marine modeling

To model and generate meteorological and marine parameters, Hidden Markov Model [3] has been selected. It is a powerful statistical tool for modeling generative sequences that can be characterized by an underlying process (called ‘hidden states’) which generates an observable sequence. In our case, hidden states can be considered as the streams temperature, sun position, etc.

HMM remains on two main assumptions:

- observed data on time t depends only of hidden states value at time t ;
- transition from one state to the next is a Markov process of order one 1.

Figure 4 shows a graphical representation of a hidden Markov model with one hidden state. S_i is the random variable modeling a hidden state that impacts Obs_i the data observed.

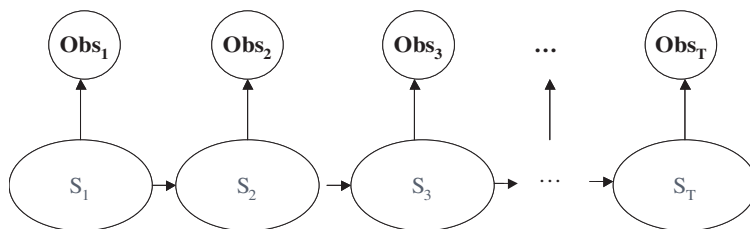


Figure 4 : Graphical model representation of a hidden Markov model

A hidden Markov model (HMM) is totally described by five elements N , M , Π , A B where:

- N is the number of hidden states ;
- M is the number of possible values taken by the future observations ;
- Π is the initial probability array of hidden states;
- A is a transition array, storing the probability of hidden state j following hidden state i ;
- B is the observation array, storing the probability of observation k being produced from the hidden state j , independent of t .

In our case, suppose we have n years of observations for our meteorological data. We consider that our parameters are independent. To limit calculation time, we break down each year of observations in m intervals, each sequence being composed of k observations. Using these sequences, we can estimate for each parameter on each interval, the HMM parameters that fits those observations :

- we evaluate Π , A B using the Baum-Welch algorithm [4] ;
- we determine N , the number of hidden states, using a BIC criterion during the Baum-Welch algorithm [5] ;
- we fix M (the number of possible values taken by the generated data) as a function of observations data and the level of precision needed.

Then we simulate different scenarii using those HMM (Figure 5). The validation process has shown that:

- seasonality of meteorological parameters is respected ;
- distributions obtained respect historical data distribution and are robust to model evaluation uncertainty (due to random initialization in Baum-Welch algorithm) ;
- variability of simulations is preserved (we do not obtain a deterministic model).

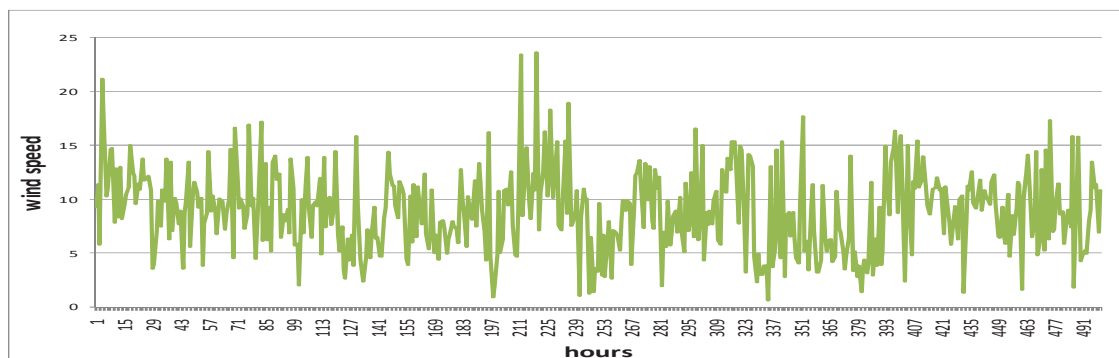


Figure 5 : simulated evolution of wind speed on the life operation of the farm

3.3. Failure modeling

3.3.1. Evaluating a failure rate

Failure rate evolution is depicted as a bathtub curve [6], i.e. evolution of failure rate follows three steps as shown in Figure 6:

- an infant mortality period where failure rate decreases ;
- a useful life period where failure rate is constant ;
- an end of life period where failure rate increases.

On each period, the failure rate follows a Weibull model with different parameters, i.e. failure rate follows the equation (1).

$$\lambda_i(t) = \beta_i * t^{\beta_i - 1} / \eta_i^{\beta_i} \quad (1)$$

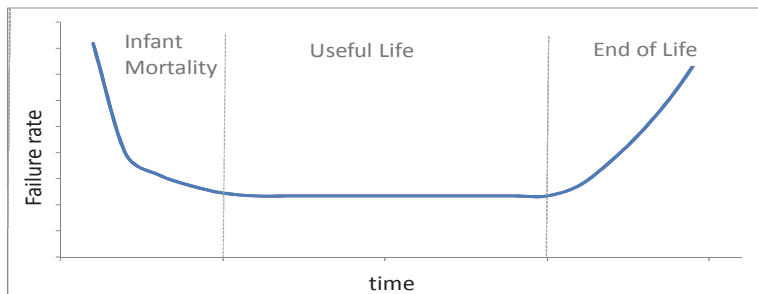


Figure 6 : Evolution of failure rate

Bathtub curve modeling is widely used in reliability engineering. It provides flexibility allowing the user:

- to consider a constant failure rate on the whole life off the wind farm (as in other offshore wind O&M costs models [2], [7], [8], [9]) when the user does not have enough feedback data ;
- to select a model closer to reality when feedback data exists or when he has a good knowledge of the degradation mechanism.

Usually we use a statistical estimation on the feedback data to evaluate the parameters β_i and η_i associated at each period. In this case, such data sets don't exist within EDF as the company has just entered the offshore wind market and is yet to have an operational windfarm. Manufacturers usually operate and maintain offshore wind farms during their guarantee period (generally, the five first years of operation). During this period, manufacturers may not communicate detailed data about O&M of the wind farm.

In order to evaluate the model parameters, EDF developed a list of pre-defined questions such as “is the component failure mechanism subject to young defaults (its failure rate decreases with time) ?”, “what is the minimal life duration of the component?”, “what is the mean failure on the life operation of the wind farm ?”, etc. The tool evaluates the bathtub curve parameters using the answers to those questions via three types of constraints : continuity constraints, constraints on the mean and constraints linked to the minimal and maximal failure dates.

3.3.2. Failure and Maintenance dates simulation

Once the parameters of the bathtub curve are calculated, we use an Event model based on Monte-Carlo simulation to evaluate different maintenance scenarii. In order to simulate the failure (or degradation) instants for an offshore wind turbine, the algorithm of the inverse transformation sampling is used. Those algorithms are already widely used in EDF's asset management methodology [10].

3.4. Advantages of event model

The introduction of an event model allows us to:

- model the O&M in a more realistic manner ;

- take into account the random behavior of the farm and the weather ;
- provide better risk indicators.

4. Conclusion and perspectives

This kind of methodology has been used for several years to help EDF's generation and engineering Divisions to make more informed investment decisions to optimize the life cycle management of their power plants.

This study proved that this methodology can be used for an objective economic valuation of offshore wind projects. Uncertainties associated to failures and unavailability are taken into account thanks to a probabilistic approach. A demonstration tool using those models will be implemented at the end of 2011.

However, some drawbacks are still remaining such as :

- computational cost of the procedure due to two kinds of simulation may lead to unstable results ;
- indicators sensibility to the input data is not characterized ;
- reliability model needs to be improved and simplified in order to reduce the number of parameters.

These issues lead to several perspectives which are :

- improvement of reliability modeling using Markov process ;
- performing global sensitivity analysis, to evaluate the influence of each input on our model outputs ;
- development of a resource optimization methodology based on the same approach.

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