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A Probabilistic approach to introduce risk measurement indicators to an offshore wind project evaluation – improvement to an existing tool

Fanny Douard¹, William Lair¹, Célia Domecq¹

¹EDF R&D, France

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.)

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

Introduction

A. 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 to 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.

B. 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 results has lower confidence than S1.

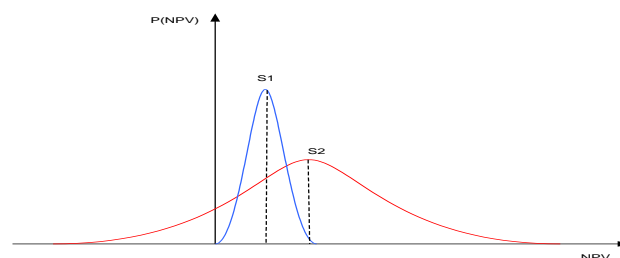


Figure 1: Strategies comparison with respect of the risk measurement indicator

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.

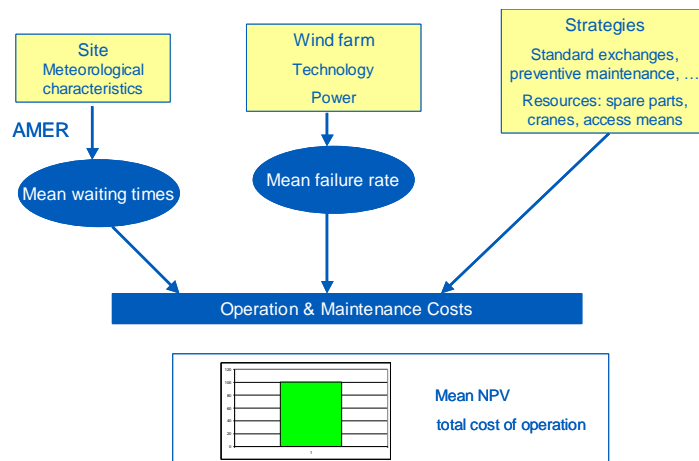


Figure 2 Actual version of ECUME

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.

ECUME IMPROVEMENTS

A. 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 is completed

- 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.

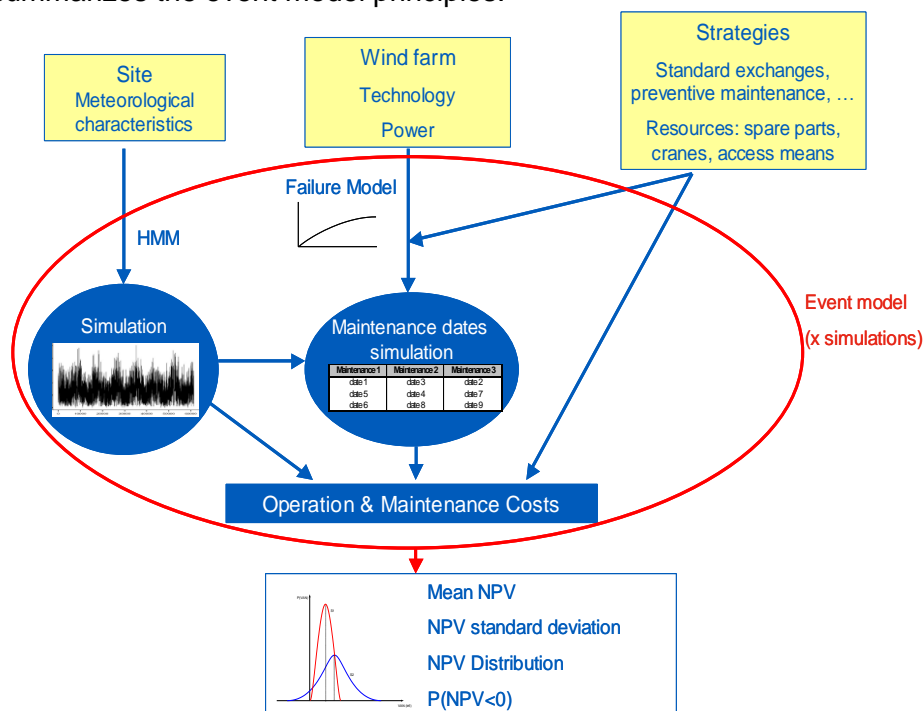


Figure 3 Event model principles

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

B. 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 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 where S_i is the random variable modeling a hidden state that impacts Obs_i the data observed.

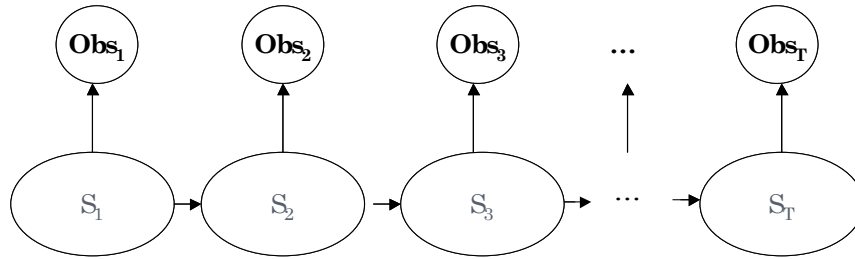


Figure 4 Graphical model representation of a hidden Markov model

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).

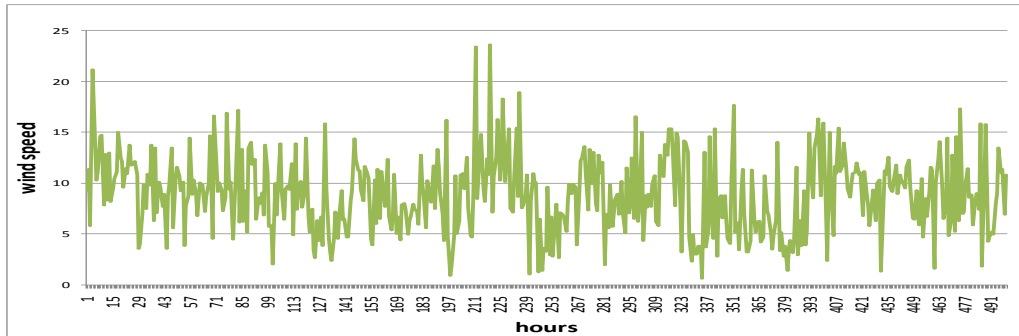


Figure 5 Simulated evolution of wind speed on the life operation of the farm

C. Failure modeling

Failure rate evolution is depicted a bathtub curve [6], i.e. evolution of failure rate follows 3 steps as shown in Figure 6:

- an infant mortality period where failure rate decreases ;
- an infant mortality 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 : $\lambda_i(t) = \beta_i * t^{\beta_i - 1} / \eta_i^{\beta_i}$.

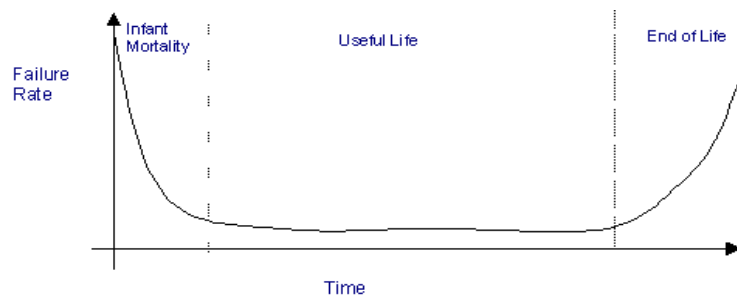


Figure 6 Evolution of failure rate

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 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. EDF 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. As shown in Figure 6, 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 failure minimal and maximal dates.

Once the parameters of the bathtub curve are calculated, we use 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].

D. 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.

Summary & Conclusion

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 has been implemented.

However, some drawbacks are still remaining such as :

- Computational cost of the procedure due to two kinds of simulation may lead to unstable results ;
- Imperfect maintenance cannot be easily modelled ;

In order to solve those issues, reliability and meteorological parameters models need to be improved and simplified. A possibility is to modelled a system degradation by a discrete state process such as Markov jump process (new – degraded – very degraded). Regarding the meteorological parameters, it is sufficient to model the waiting time before a weather window ; a possibility is to model the state of these parameters by a semi-Markov process with two states (good – not good).

Other perspectives are to perform global sensitivity analysis, to evaluate the influence of each input on our model outputs and to develop a resource optimization methodology.

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Generation capacity adequacy assessment and incentives for investment under uncertainty

Chris Dent

Durham University, UK
chris.dent@durham.ac.uk

Motivation

Generation adequacy assessment, i.e. evaluating the risk that insufficient generating capacity will be available to support extreme demands, has long been a key part of power system planning (see [1] for a general survey of methodologies used, and [2] for a survey of current industry practices.) In monopoly (e.g. [3]) and some liberalised systems (e.g. [4]), such assessments are used to set requirements for installed generating capacity.

The Great Britain electricity system does not at present have a centrally determined capacity requirement. The current market design presumes that the revenue that generating companies (GENCOs) earn through trading energy will incentivise sufficient capacity investment. There are doubts as to whether this will in fact prove to be the case, as some required 'peaking plant' may run very infrequently at times of low generation availability and extreme demand, creating very high investment risk. This is particularly important in a system with high installed variable-output renewable capacity, which reduces opportunities for conventional generating plant to run, without decreasing to the same extent the required installed conventional capacity (for an example of how the distribution of conventional capacity requirement over a year can change with a high wind penetration, see [5].)

In response to this and other concerns, such as whether the current market can deliver the sheer volume of investment required to replace ageing plant, the UK government is considering introducing a capacity mechanism [6] (the general name given to explicit incentives for generation investment within an electricity market). Annex C to the Government's Electricity Market Reform White Paper [7] sets out the options considered, and the decision document at [6] sets out the latest official position.

Partly in preparation for a future capacity mechanism, the government has already mandated a capacity assessment report to be produced annually by the regulator Ofgem, looking four years ahead of the publication date [8]. This forms the framework for the GB study discussed here.

Wind Generation in the Great Britain Statutory Capacity Assessment Study

The technical modelling for the capacity assessment report has been delegated to National Grid in its role as GB System Operator; they have contracted C.J. Dent (author of this survey) and S. Zachary (Heriot-Watt University) to assist with the necessary probabilistic and statistical modelling. Public updates on the project from Ofgem are available at [9].

The treatment of demand and conventional plant within this study is fairly standard; the demand at a snapshot in time is modelled as a random sample from the historic peak season record, and the distribution of available conventional capacity is constructed from distributions for each individual unit by convolution (commonly termed the capacity outage table approach [1]).

The treatment of wind generation within the study will be described in more detail here. The most common approach to including wind generation in adequacy assessments is the so-called hindcast approach (see for example the IEEE 'Capacity Value of Wind Power' Task Force paper), in which the historic time series of demand and available renewable resource are used directly in the risk calculation. For instance, the Loss of Load Expectation (expected number of periods in which there is a shortage) would be calculated as:

$$[LOLE] \propto \sum_t P(X + y_t < d_t)$$

where (d_t, y_t) are the demand and available renewable resource at historic time t (appropriately rescaled to the future system scenario under study), and X is the available conventional capacity at a snapshot in time (a random variable).

In GB however, with a substantial wind penetration the results of such a hindcast calculation are dominated by a small number of historic records with high demand and low available wind resource. This may be seen by breaking down the calculation results into contributions from each historic record, and the consequences for uncertainty in the final result may be explored by bootstrap resampling. For a preliminary exploration of these matters see [11].

More generally, the historic data are entirely inadequate in GB to make a quantitative assessment of any statistical relationship which might exist between demand and available wind capacity at times of extreme demand. For the GB capacity assessment study, the available wind capacity at a future snapshot in time will be modelled as the combination of the wind resource at a randomly chosen time in the available historic record of peak-season wind resource, combined with the projected installed wind capacity at the future time studied; within the probabilistic model, independence between demand and available wind capacity, conditional on being within the peak season, is assumed. The wind resource dataset for the 2012 study is based on NASA's MERRA reanalysis [12].

A common concern in the GB power systems community is that extreme demands might typically be associated with a high pressure area over Britain, which would be associated with low available wind capacity. [13] demonstrates however that the highest demands in GB are typically associated with a high pressure area to the north or east of GB, advecting cold air from continental Europe. This is a more optimistic picture, as it suggests that extreme demands are associated with at least some wind in the south of GB, and certainly suggests that extreme cold periods are unlikely to be consistently calm.

It is most likely that the uncertainty in the final calculation result arising from the treatment of wind will be dominated by modelling uncertainty (the need for this assumption of independence within the probabilistic model due to sparsity of data), rather than sampling

uncertainty (the consequences, for a given estimation process, of a finite size dataset). The consequence of this modelling uncertainty may be assessed by a conservative rescaling of the distribution of available wind capacity.

Dissemination of Final Modelling Results and Methodology

The 2012 study is still in progress at the time of writing; National Grid are due to present their modelling study to Ofgem at the start of June 2012, and Ofgem present their capacity assessment to the Government at the start of September. Further technical detail of the final methodology will be presented in the following specific locations:

- The presentation by C.J. Dent at the 2012 Probabilistic Modelling Applied to Power Systems conference, associated with the paper [11].
- The IEEE LOLE Working Group meeting at the 2012 IEEE Power and Energy Society General Meeting in July 2012; this presentation will be archived on the WG website.

Publication plans for the official capacity adequacy study results have yet to be finalised.

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Reliability Analysis of Electrical Systems for Offshore Wind

Rachel Hodges¹, Russell Bryans²

¹TNEI Services, United Kingdom

rachel.hodges@tnei.co.uk

²TNEI services, United Kingdom

russ.bryans@tnei.co.uk

Abstract

Studies undertaken by TNEI have identified that decisions on the optimum design of a windfarm are extremely sensitive to assumed reliability and repair data and in general, only a limited amount of statistical information is available in the public domain in relation to the faults in the electrical system (array and grid connection) that make up an offshore windfarm.

There are a number of published reports that have attempted to collate publicly available data from existing windfarms and then analyse repair time issues and failure rates but they offer a wide range of potential failure rates and repair times. When these figures are used in undertaking a cost benefit analysis of electrical infrastructure design then the assumed availability parameters can significantly affect the results, leading to different designs chosen and not necessarily the most optimal.

This paper shows the results of a windfarm design study with sensitivity analysis undertaken on the reliability and availability data to show the impact on the lifetime costs and therefore the optimal design choice.

The aim of the paper is to promote discussion within the industry and highlight the key importance of gathering this key data resource. It will also inform all involved in offshore windfarm electrical system design on the key factors that need to be considered to provide a robust system design.

Keywords – Reliability, Availability, Offshore Wind, Data Sources, Optimal Design.

Introduction

Reliability and availability of an offshore windfarm electrical system is dependent on the reliability and availability (failure rate and mean time to repair, MTTR) of the individual system components and their arrangement. It is critical to understanding asset utilisation, maintenance planning, redundancy and strategic spares.

The issue is that there is little long term experience with the operation of offshore windfarms and the ones that have been built are smaller and closer to shore than those that are currently under construction and in the design stages. There is some data on the operation of power equipment in a marine environment from the oil and gas industry and operational data from onshore installations and subsea transmission links can provide some additional guidance.

Reliability data from offshore windfarms may be artificially high due to teething problems typically experienced in the first few years of operation. Published offshore failure rate data is often given in ranges and this can produce large variations in reliability values. In addition, adverse weather conditions can restrict access to offshore assets, increasing transport and repair times significantly. Time spent waiting for a suitable 'weather window' to enable access by marine vessels increases the average MTTR of offshore transmission assets. Whereas, in an indoor onshore substation, repair may take a matter of hours or days, for offshore sites this may be closer to months.

Failure and Repair Data Sources

Studies undertaken by TNEI to assess potential options for the reduction of electrical connection lifecycle costs have identified that decisions on the optimum design of a windfarm are extremely sensitive to assumed reliability and repair data and in general, only a limited amount of statistical information is available in relation to the faults in the electrical systems of an offshore windfarm.

There are a number of published reports that have attempted to collate publicly available data from existing windfarms and then analyse repair time issues and failure rates but they offer a range of potential failure rates and repair times.

Example for Illustration

The Upwind report [1] provided indicative failure rates for various components and estimated that the internal grid cables have a failure rate of 0.015/ year x km and a repair time of 1440 hours but then it goes on to explain that experience derived from offshore windfarms in operation shows that cable failures seem to be less frequent than expected according to theory and experience in other sectors.

For DONG Energy's and Vattenfall's portfolios of offshore windfarms, an assessment undertaken in 2006 of the total cable lengths and the number of years of operation without failures indicated that failure rates could be significantly reduced compared to what was expected in previously assessed generic values, e.g. based on experience from high-voltage DC-links. But it would only take 8 failure events to increase this failure rate to the 0.015 estimated above and another 5 years of operation without failure to decrease this failure rate to 0.0008.

Internal Grid Cables	km	Commissioned Year	Years of operation	km × year	1/(km × year)
Tunø Knob	8	1995	11	88	
Middelgrunden	9	2000	6	54	
Horns Rev	60	2002	4	240	
Nysted	48	2003	3	144	
Kentish	20	2005	1	20	
Total				546	0.002

Table 1 – Windfarm Array Cable Failure Rates

This reduced probability of failures can be justified by the following elements:

- Cables are buried. It has been normal practice in windfarms to use cables embedded in the seabed to provide protection.
- Windfarms are currently, mostly located in shallow waters.
- Cables between wind turbines are easier to identify by fishing/ship traffic.

When undertaking cost benefit analysis on electrical infrastructure then figures ranging from 0.015 to 0.0008 failures per km per year could be used to assess the options and this would give a very wide range of results.

Variation in Failure Rates and Repair Times

As further examples, estimates, based on published data [1],[2],[3],[4],[5] of mean time to repair equipment located on offshore substations and associated with offshore transmission are shown in Table 2.

It can be seen from this table that there is a large variation in data used and this data was collated based on a variety of experiences. They range from large CIGRE studies and joint inter-developer experiences to individual manufacturer data and considered opinion of academics. Where similar figures are used in different papers then they can often be traced back to the same initial studies and papers and this is due to an overall lack of data.

	Min Failure Rate / year	Max Failure Rate / year	Min MTTR	Max MTTR
Export Cable	0.00021/km	0.015/km	6 days	2 months
Array Cable	0.0008/km	0.015/km	6 days	2 months
Turbine Transformer	0.0131		10 days	
Offshore Transformer	0.019	0.03	6 months	
Grid Transformer	0.019	0.02	2 months	6 months
Circuit Breaker	0.025		10 days	

Table 2 – Component Failure Rates and MTTR

The mean time to repair will be significantly impacted by the availability of spares, repair vessels, personnel and very importantly, weather conditions. Therefore, it is understandable that these figures may vary widely and this needs to be considered carefully when making initial design decisions.

Planned Maintenance

In addition to failures, planned or scheduled maintenance has an impact on availability of the windfarm. Unlike failures, maintenance outages are controllable but still result in a reduction in capacity, albeit hours rather than days. This will not be considered further here as the planned maintenance times are a function of the chosen electrical configuration and operation and maintenance plan but will not be impacted by the reliability data or significantly by the availability calculation method.

Redundancy and Configuration Options

Availability of any system is, in addition to component reliability, subject to the system architecture or configuration.

Some of the configuration options that can be considered to improve availability on an offshore windfarm are:

- Provide duplicate, redundant onshore transformers, export cables and offshore transformers and interconnection so that in the event of a failure, export from the windfarm, albeit not necessarily full export capacity, can still be achieved.
- Install looped array cables (either fully redundant rings or partially rated loops) so that if a cable is damaged the wind turbine can still export through the other side of the loop.
- Decrease the number of turbines that are supplied on each radial string or include branches on each string
- Increase the number of offshore substation platforms
- Increase the availability of spares, repair vessels and maintenance personnel.

Redundancy

Clearly, where availability is considered a major issue, then fully redundant equipment can be installed at a cost. Options include installing 2 x 70% transformers, 2 x 100% transformers or additional transformers in a 3 x 50% arrangement. Similar options exist for cables. Double busbar switchgear leads to increased availability although this will not be considered further here as the arguments for double busbars have clearly been made in an onshore environment and make just as much, if not more sense in an offshore environment. Cross connection of platforms has considerable impact, allowing an alternative route for export in the event of a fault for only the cost of a short length of cable and additional switchgear.

Full redundancy leads to a significant improvement in availability (100% when only considering single, independent outages) but at considerable additional cost. The actual level of redundancy is a matter of approach to risk which, in the case of offshore windfarms is confidence in the numbers.

Methods of Calculating Availability

Availability calculations can be undertaken using either deterministic or probabilistic methods and considering varying levels of concurrent failure (N-1, N-1-1, N-2 etc) and accuracy.

There have been a number of studies that attempted to undertake a full monte-carlo analysis of the windfarm, taking into account the wind distribution, power output of the wind turbines, probabilities of component failure, expected 'lost' energy, availability of vessels and wave heights for access but using this type of analysis means that the comparison of numerous configuration, layouts and data sources would be extremely time consuming and it can lead to an overly sensitive analysis of the situation. It assumes that failures are independent from one another but it is often the case that the failures are related to manufacturing quality, installation procedures, and environmental conditions and so are actually not independent. TNEI have built up these types of models for analysis but have found that the results are inconsistent and so comparisons between topologies and data sources are very, very difficult to assess.

There have also been studies that use a very simple approach which indicates only the risks associated with each configuration and aims to rank them but without being able to clarify the actual overall expected impact of the choice on the lifecycle costs to the project.

In the GB system, the OFTOs use a loss of capacity approach, for example if there are two cables, each rated at 70% of the rated capacity of the windfarm and one of them is unavailable then the lost capacity would be 30%. But the developer is more likely to consider a loss of revenue or curtailment of export which takes into account load factors, overload capability and dynamic ratings, all of which would increase the transmission system availability.

TNEI have chosen to use a middle ground approach that considers the chosen set of Mean Time To Repair (MTTR) and Mean Time to Fail (MTTF) data and then undertakes availability calculations based on a "full-year" approach which takes into account the wind duration curves and turbine power curves. This method considers each component individually and then combines the values to provide the total unavailability. This assumes that all component failures occur individually but in real life they may occur concurrently meaning that an array cable failure may occur at the same time as a grid transformer and the energy will not be lost twice in this circumstance. Therefore the total availability may be lower than it actually would be in real-life but this would be difficult to avoid without undertaking a full monte-carlo analysis.

This method allows the assessment of any part-load benefits and partial/full cable and transformer redundancy, as well as providing information on the maximum loading of individual cable circuits for the cable rating assessment which is particularly important for the J/I tube constraints.

The results are presented as lost MWh per year and as a percentage of annual output and these results are then used to assess the lost revenue on an NPV basis to determine which configuration gives the lowest overall cost.

Studies Undertaken

In order to demonstrate the impact of the data source and how these can significantly affect the outcomes of analysis, the following studies have been undertaken on a 1000MW windfarm with 278, 3.6MW wind turbines and 3 offshore substations each with 92 or 93 turbines connected into them.

Option No.	Option Descriptor	Grid Transformer	Offshore Transformer	Export Cables / platform	Substation Inter-connection	Array Cable
1	Base Case	2 x 50%	2 x 50%*	1	None	String
2	Improved Grid Tx	2 x 70%	2 x 50%	1	None	String
3	Duplicate Grid Tx	2 x 100%	2 x 50%	1	None	String
4	Improved Offshore Tx	2 x 50%	2 x 70%	1	None	String
5	Duplicate Offshore Tx	2 x 50%	2 x 100%	1	None	String
6	Smaller Offshore Txs	2 x 50%	3 x 33%	1	None	String
7	Triplicate Offshore Txs	2 x 50%	3 x 50%	1	None	String
8	Duplicate Cables	2 x 50%	2 x 50%	2	None	String
9	Interconnected	2 x 50%	2 x 50%	1	Interconnected	String
10	Fully Redundant Rings	2 x 50%	2 x 50%	1	None	Ring
11	Partially Rated Loops	2 x 50%	2 x 50%	1	None	Loop
12	Full Redundancy	2 x 100%	2 x 100%	2	Interconnected	Ring

Table 3 – Windfarm Design Configurations

*This is the minimum requirement to meet SQSS requirements in GB system.

The following cases were used to show the impact of reliability:

	Worst Case	Mid Case	Best Case
Export Cable Failure Rate	0.015/km/year	0.0094/km/year	0.00021/km/year
Export Cable MTTR	3 months	2 months	1 week
Array Cable Failure Rate	0.015/km/year	0.0094/km/year	0.0008/km/year
Array Cable MTTR	3 months	2 months	1 week
Turbine Transformer Failure Rate	0.025/year	0.0131/year	0.0131/year
Turbine Transformer MTTR	20 days	20 days	10 days
Offshore Transformer Failure Rate	0.03/year	0.019/year	0.019/year
Offshore Transformer MTTR	6 months	6 months	3 months
Grid Transformer Failure Rate	0.03/year	0.019/year	0.019/year
Grid Transformer MTTR	6 months	6 months	2 months
Circuit Breaker Failure Rate	0.025/year	0.025/year	0.025/year
Circuit Breaker MTTR	1 month	20 days	10 days

Table 4 – Range of Component Failure Rates and MTTR

Comparison of Results

Using a discounted rate of 8%, an inflation rate of 1.5%, and an energy value including ROCs of £100/MWh, the NPV of lost energy over 25 years was calculated and the savings in lost revenue were compared to the increased capital costs to determine which configuration has the best overall lifecycle costs.

The results are presented in Tables 5 and 6 and also in Figures 1, 2 and 3.

Option No.	Option Descriptor	Capital Costs (million)	Availability		
			Best	Mid	Worst

1	Base Case	£473	99.09%	89.08%	76.12%
2	Improved Grid Tx	£477	99.20%	89.38%	76.59%
3	Duplicate Grid Tx	£483	99.26%	89.58%	76.90%
4	Improved Offshore Tx	£483	99.21%	89.31%	76.48%
5	Duplicate Offshore Tx	£507	99.34%	89.57%	76.87%
6	Smaller Offshore Tx	£493	99.17%	89.24%	76.36%
7	Triplicate Offshore Tx	£510	99.34%	89.57%	76.87%
8	Duplicate Cables	£645	99.16%	97.06%	94.47%
9	Interconnected	£503	99.13%	93.88%	87.16%
10	Fully Redundant Rings	£592	99.47%	90.78%	79.17%
11	Partially Rated Loops	£489	99.21%	89.55%	76.96%
12	Full Redundancy	£808	99.96%	99.92%	99.84%

Table 5 – Availability for Different Configurations

Option No.	Option Descriptor	Life Cycle Costs (millions)		
		Best	Mid	Worst
1	Base Case	£518	£1,022	£1,695
2	Improved Grid Tx	£517	£1,010	£1,675
3	Duplicate Grid Tx	£519	£1,006	£1,665
4	Improved Offshore Tx	£522	£1,020	£1,686
5	Duplicate Offshore Tx	£539	£1,031	£1,690
6	Smaller Offshore Tx	£534	£1,034	£1,703
7	Triplicate Offshore Tx	£543	£1,034	£1,693
8	Duplicate Cables	£687	£792	£922
9	Interconnected	£546	£810	£1,156
10	Fully Redundant Rings	£618	£1,048	£1,624
11	Partially Rated Loops	£528	£1,012	£1,658
12	Full Redundancy	£810	£812	£816

Table 6 – Life Cycle Costs for Different Configurations

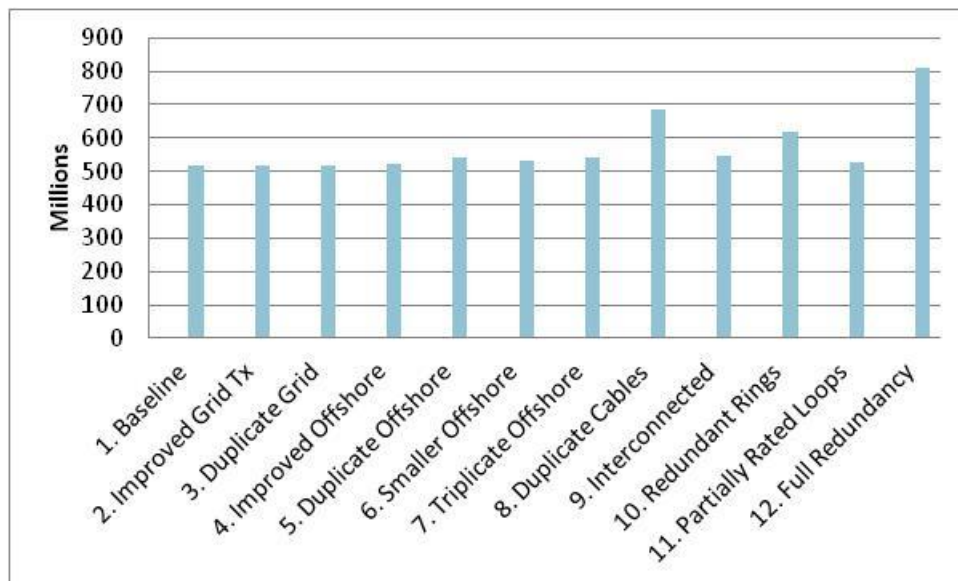


Figure 1 – Overall Lifecycle Costs using Best Case Availability Figures

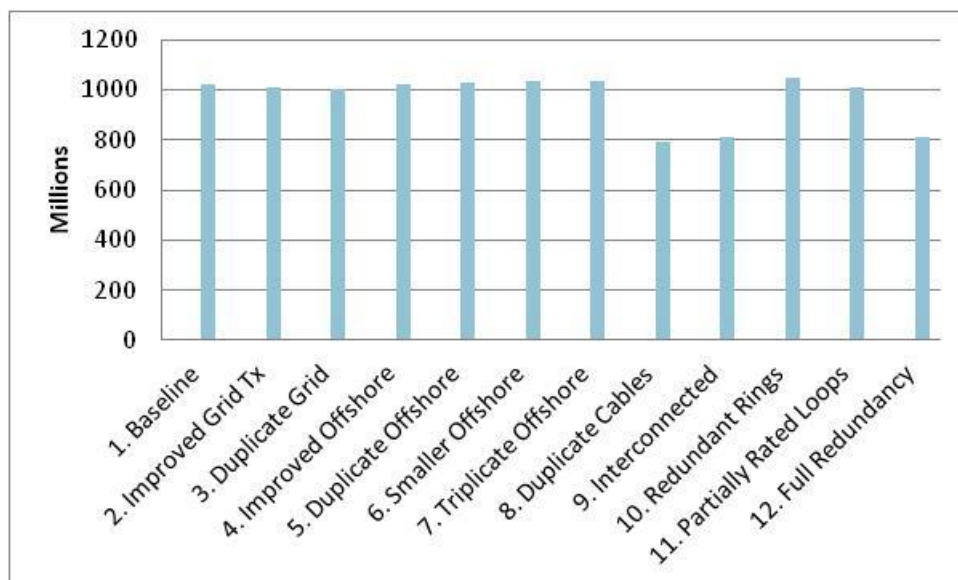


Figure 2 – Overall Lifecycle Costs using Mid Case Availability Figures

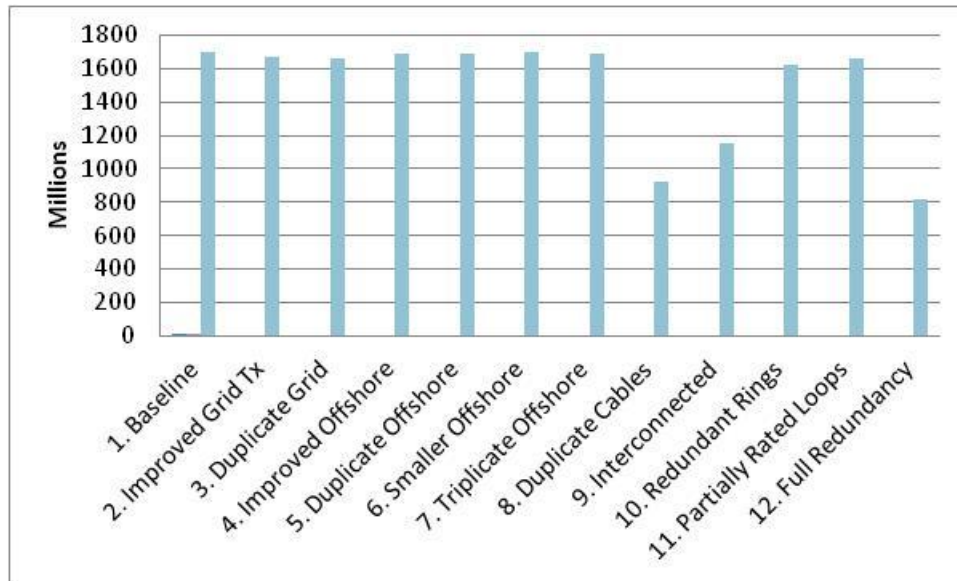


Figure 3 – Overall Lifecycle Costs using Worst Case Availability Figures

Summary & Conclusion

Compared to the baseline configuration then given the best case availability figures then the only change that may be considered to improve the lifecycle costs of the windfarm is to slightly over-rate the onshore grid transformers. This would reduce the costs by only £1 million but it would also have a beneficial effect on the losses in the transformer.

Other options may be considered for other reasons – cable loops reduce the need for diesel generators on the turbines etc.

Given the mid case availability figures then the main changes that would be considered to improve lifecycle costs of the windfarm are:

- Duplicate Grid transformer or at least improved grid transformer – reduction of £15 million or £11 million.
- Improved offshore transformer – reduction of £2 million.
- Duplicate cables to shore or at least interconnected substations – reduction of £230 million or £212 million.
- Partially rated loops – reduction of £10 million.

The total lifecycle costs could be £765 million, a reduction of £257 million from the baseline, if all of these options were implemented.

Given the worst case availability figures then the main changes that would be considered to improve lifecycle costs of the windfarm are:

- Duplicate Grid transformer – reduction of £30 million.
- Improved offshore transformer – reduction of £9 million.
- Duplicate cables to shore – reduction of £773 million.
- Fully redundant rings – reduction of £71 million.

The total lifecycle costs could be £812 million, a reduction of £883 million from the baseline, if all of these options were implemented.

As the availability figures that are to be experienced by the windfarm are currently unknown then the developer is forced to try and make a robust decision with the information that they have.

If they believe the best case figures and chose to implement a windfarm design with only a slightly improved grid transformer then the risk is that instead of the overall lifecycle costs of £517 million they actually experience very unfavourable availability figures and experience an overall lifecycle cost of £1,675 million, £863 million more than they would have experienced if they were to install a duplicated and redundant electrical system.

If, on the other hand, they believe the worst case figures and chose to implement a windfarm design with a duplicated and redundant electrical system then the overall life cycle costs will be quite predictable but they will have paid an additional £311 million in equipment capital costs compared with the least cost option and may never experience high failure rates.

These issues are summarised in Table 7 below.

Which data do I believe?	Configuration Choice based on that data	Range of Life Cycle Costs (millions)		
		Best	Mid	Worst
Best	Improved Grid Transformer	£517	£1,010	£1,675
Mid	Duplicate Grid, Improved Offshore, Duplicate Cable, Loops	£702	£765	£847
Worst	Duplicate Grid, Improved Offshore, Duplicate Cable, Rings	£793	£801	£812

Table 7 – Summary of Decision Risks

The main conclusion to draw from these results is to support the optimal design of offshore windfarms then more data on the expected reliability and availability of components in the offshore environment need to be recorded, collated and analysed. This will allow developers and designers to make more informed decisions at the design stage and will remove some of the risks to the long term costs of energy.

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Offshore Wind Farm Business Case: What Do we Mean by Availability and Why is it Important to Measure its Uncertainty?

Athena Zitrou , Tim Bedford, Lesley Walls

Department of Management Science, University of Strathclyde, UK

Abstract

Since offshore wind farm availability is related to yield, availability predictions are crucial in attracting the investment in wind projects necessary. Effective availability analyses require a clear view of the term ‘availability’; nevertheless, there no consistent definition or calculation of availability in the literature and wind industry alike. Such ambiguity may have an impact on financial analysis results and jeopardise the economic viability of offshore wind projects. In this paper we discuss availability in general and in the wind industry in particular. We identify the reasons that have led to discrepancy in availability analyses, and define an availability indicator that addresses these. The suggested indicator describes wind farm performance in terms of output, and can be used meaningfully within a financial context. Given the high-risk nature of offshore wind technology, we stress the importance of modelling uncertainty. We discuss the sources and types of uncertainty, and use a simple example to illustrate the impact of modelling uncertainty in availability predictions on financial decisions.

Keywords – wind farm, availability, uncertainty, epistemic, aleatory

Introduction

The offshore wind industry has seen rapid growth and received considerable investment from both government and private sector in recent years. This is true especially in the UK, where offshore wind plays a dominant role in the government’s renewable energy portfolio [1]. For the UK to meet its energy targets, offshore wind farms need to be developed and operated successfully. A prerequisite for the successful development of offshore wind farms is the availability of finance, which needs to be secured through investment at a pre-construction phase. Investment can only be attracted if appropriate understanding of the economic characteristics of the project over its entire lifetime is gained. This is the reason that a detailed analysis of costs and revenues is of key importance.

Offshore wind farms are capital-intensive projects: the cost of wind turbines, foundations and grid connection is high compared to onshore counterparts and account for as much as the 70-80% of total costs [2, 3]. Nevertheless, these costs can be evaluated with relative confidence during the construction phase [4]. On the other hand, the costs and revenues related to the performance of the wind farm (i.e. Operation and Maintenance (O&M) costs and energy generation) from installation until the end of life are variable. The early stages of

operation of a wind farm (from installation to end of warranty) are particularly important since, typically, this is a period of 'growth' for the farm. This is because offshore wind technology is relatively young with few offshore wind turbines having reached maturity levels. During early life manufacturers and operators gain an understanding of the particular issues that arise, and resolve teething problems by performing a variety of technical and operational adaptations. Therefore, it is important that the uncertainties related to this period of the project are sufficiently understood and their impact on the variable costs appropriately analysed.

The overall performance of an offshore wind farm is strongly related to its 'technical' performance, which is typically measured in terms of availability. To this end, a comprehensive availability analysis is key in predicting the long-term characteristics of an offshore wind farm. Effective availability analyses require a clear definition of availability. In general, the literature provides such definitions, however, these are either too generic or describe the performance of a wind turbine rather than the performance of a wind farm. Moreover, the definitions of availability depend largely on the perspective of the different stakeholders, such as manufactures, operators, developers etc. As a result, there is doubt about reported availability figures as analyses often fail to provide a realistic description of the farm's actual performance [5]. Most availability analyses are concerned with point estimates [6, 7] of availability indicators. Given the high-risk offshore wind technology, there is a need to quantify the state-of-knowledge uncertainty on offshore wind availability estimates. Financial analyses that provide uncertainty bounds rather than point estimates of availability allow decision-makers to consider wind farm performance according to their own approach to risk, and assess the effect of reducing this uncertainty. For instance, risk-averse decision-makers may choose to use lower bound availability estimates in their analyses to reduce the likelihood of systematic overestimations of performance and yield that can jeopardise the economic viability of the project.

This paper focuses on the evaluation of offshore wind farm technical performance, in particular over the early operating stages of the project, i.e. from installation to end of warranty. We discuss the different definitions of availability found in the literature in general and for wind systems in particular, and suggest a performance indicator that is meaningful for assessing the performance of a wind farm. We highlight the need for appropriate uncertainty analysis that will allow decision-makers to understand the sources of uncertainty and mitigate risk.

Measuring Wind Farm Performance

Within the literature a number of performance measures have been suggested for the evaluation of power systems [8]. Table 1 presents a selection of metrics that, even though generally defined, are used most frequently in the evaluation of wind power systems. [7, 9, 10]. The capacity factor is the fraction of the actual energy produced over the maximum power that can be generated over ideal wind conditions. It is concerned with the evaluation of the power output of a farm by considering the stochastic nature of the wind resource. On the other hand, performance measures such as the Loss of Load Probability (LOLP) and

Loss of Load Expectation (LOLE) consider aspects external to the system, such as the load subjected to the wind farm.

To allow for the accurate evaluation of power generation systems, it is important that metrics like the ones mentioned earlier are integrated with measures of technical performance such as availability. This will allow for the consideration of all factors influencing the system, such as the repair and failure processes. Especially when it comes to wind power systems, availability has been extensively used to assess the value of a wind farm [6, 7, 9]. In the offshore wind case for example, investors expect a long-term offshore availability of 97%, a level that is currently achieved on land [11]. In the next section we will discuss availability in general and within the wind industry in particular, and explore the problems that relate to its definition and calculation.

Table 1: Performance metrics for an offshore wind farm.

Index	Description
Capacity Factor (CF)	Percentage of power actually generated relative to the hypothetical maximum possible (i.e. running full time at rated power).
Loss of Generation Ratio Probability (LGRP)	Probability that at least certain percent of wind power cannot be passed into the system
Loss of Load Probability (LOLP)	Probability of experiencing a loss of load event (load exceeding available generation).
Loss of Load Expectation (LOLE)	Expected accumulated amount of time during which a shortage of power is experienced.
Loss of Energy Expectation (LOEE)	Expected energy that will not be supplied due to a loss of load event
Loss of Load Frequency (LOLF)	Expected frequency of encountering a loss of load event in a given period
Loss of Load Duration (LOLD)	Expected duration of a loss of load event

A. Availability as an indicator

Availability is a performance measures for repairable systems [12]. The term availability refers to the "ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided" [IEC Glossary]. In the literature one can find definitions for a number of availability-related indicators for repairable systems in general [13, 14]. Let

$$X(t) = \begin{cases} 1: & \text{if the system is up at time } t \\ 0: & \text{if the system is down at time } t \end{cases} \quad (1)$$

Point availability is the probability that the system is available at a given instant and it is given by

$$A(t) = Pr[X(t)=1] = E[X(t)]. \quad (2)$$

Within the wind power industry, there are two prevailing definitions of availability: turbine availability and system availability [6]. Turbine availability describes the fraction of time that the turbine is able to produce energy and is the focus of contractual warranty agreements between wind farm owners and wind turbine manufacturers. It reflects the manufacturer's perspective, and it does not consider downtime due to balance of plant faults or weather conditions, even if an internal fault is present. As described earlier, planned maintenance is not considered by manufacturers [5]. System availability describes the performance of the wind farm as a whole; it is interpreted as the proportion of time that the entire farm generates and delivers electricity to the grid and considers all possible interruptions (including failures in the balance of plant and planned maintenance). It is important to note that these two terms are not standardised, and may be found to describe different concepts in different analyses [7, 11]. Reported figures on availability often correspond to different background calculations [5], making it difficult to compare performance across wind systems and often leading to inaccurate performance assessments.

Successful analyses require an unambiguous definition of availability. Definition (1) describes the system in a binary manner: it can either be failed ('down') or operating ('up'). Whereas this may be appropriate for components, it is often unsuitable when it comes to describing multi-component systems such as wind farms. Consider a farm half of whose turbines are operating at some point in time and half are not. Is the overall system (farm) in an 'up' or in a 'down' state at time t ? The difficulty in characterising a farm as functioning or not makes problematic the definition of point availability for a farm as given in (2). But even when it comes to describing performance at a wind turbine level, a two-state definition may not be appropriate. Internal or external conditions may inhibit the turbine from functioning at its full efficiency. For example, a fault in the pitch system can lead to problematic alignment of the blades. This may not render the turbine inoperable, but unable to generate electricity at its full capacity. Therefore, there is a need to define intermediate states to describe the operating condition of a wind turbine, and describe how these states affect the performance of the turbine and the farm as a whole.

It is also important to consider the overall context of the analysis. Wind system manufacturers, operators and project developers are all interested in availability analyses; however, each party has different objectives, and as a consequence, different views on when a system is 'available' or not. To be more precise, there are circumstances when a wind turbine is technically able to generate electricity, but it is not actually doing so. This could be due to the wind resource being out of specifications, because of scheduled shut-downs of wind turbines due to maintenance or because of problems in the grid. Manufacturers consider only events that are under their control when they estimate availability, and omit these circumstances for their availability estimates. In their calculations a turbine is 'functioning' when the wind is out of range or during planned maintenance, even

if there is no electrical output or a turbine fault exists. Operators, on the other hand, are interested in all events that interrupt operability, regardless of the cause. In their analyses all maintenance activities (corrective or planned) and type of fault count towards downtime. Since there are no universally agreed guidelines as to what type of events count towards uptime and downtime, there is inconsistency in the availability estimates produced and not all availability figures reflect actual performance.

The need for an unambiguous definition of availability has not gone unrecognised. An International Electrotechnical Commission working group has been formed in 2007 [7] to provide guidance to availability analyses in the wind industry. A technical report has been published in 2011 [15] and is concerned mainly with the assessment of wind turbine availability. The standard provides suggestions as to what should count as uptime or downtime at a turbine level and provides a distinction between fully and partially operating turbines. However, there is no differentiation between the effect of different operating states on performance. Therefore, the pitfall described above still remains.

Next, we define an availability indicator for an offshore wind farm that can be used meaningfully to support availability predictions used in financial analyses at a pre-construction stage and in the assessment of revenue. Revenue is closely associated to the technological performance of the farm as a whole. Availability analyses need to consider all events that interrupt power generation, including all types of maintenance and type of failure. The suggested indicator integrates technical performance with producibility. To do so, the effect of partially operating states on system performance is clearly defined, addressing the issue of duality in system characterisation.

A. Farm availability indicator

Consider a wind farm comprising of n wind turbines. We define the *point* availability-informed capability at time t to be the fraction

$$C(t) = \frac{OP(t)}{IP(t)} \quad (3)$$

where $OP(t)$ is the maximum output power, given the operating condition of the turbines comprising the farm, and $IP(t)$ is the installed power of the farm at time t . The *average* farm availability-informed capability over some interval (τ_1, τ_2) is given by

$$C_{(\tau_1, \tau_2)} = \frac{1}{\tau_2 - \tau_1} \int_{\tau_1}^{\tau_2} C(t) dt = \frac{1}{nP_1} OP_{(\tau_1, \tau_2)} \quad (4)$$

where $OP_{(\tau_1, \tau_2)}$ is the average maximum power output per unit of time over (τ_1, τ_2) , given the operating condition of the turbines comprising the farm. It is often of interest to assess the proportion of time over interval (τ_1, τ_2) that the farm is operating at an acceptable level.

Therefore, we define the *level* availability-informed capability over interval (τ_1, τ_2) to be the proportion of time $C(t)$ is above some acceptable level L , viz.

$$C_{(\tau_1, \tau_2)}(L) = \frac{1}{\tau_2 - \tau_1} \int_{\tau_1}^{\tau_2} 1\{C(t) > L\} dt. \quad (5)$$

where $1\{\cdot\}$ is the indicator function. If $C_{(\tau_1, \tau_2)}(L) = k100\%$, then this means that $k100\%$ of the time over (τ_1, τ_2) the farm's maximum output exceeds $L\%$ of the installed power.

The power generated in the farm is equal to the sum of the power generated by the individual turbines, so

$$C(t) = \frac{\sum_{i=1}^n OP_i(t)}{nP_i(t)} \quad (6)$$

where $OP_i(t)$ and $IP_i(t)$ is the output power and installed power of turbine i at time t respectively, $i=1, \dots, n$. As discussed in the previous section, a wind turbine [15]. Suppose that the wind turbine has $m+1$ different operating states, where state m is full operation and state 0 is out of operation. We use stochastic process $\{X_i(t), t \geq 0\}$ with state space $\{0, 1, \dots, m\}$ to model wind turbine i (where $X_i(t) = j$ if turbine is in operating condition j). To represent the effect of different operating conditions on the output, we define different power curves. Each power curve characterises the power output from a wind turbine at a given operating state (see Figure **Error! Reference source not found.**). Note that when the turbine is in a perfect state (State m), then the output power coincides with the rated output power.

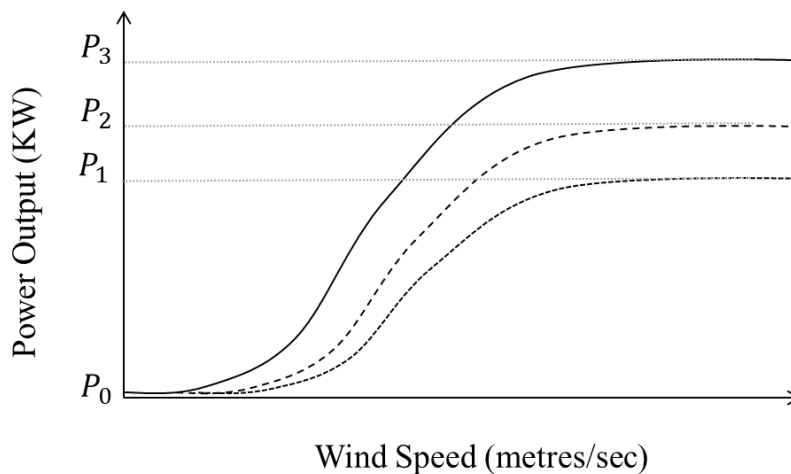


Figure 1: Power curves corresponding to different operating states. State 3 corresponds to a turbine operating fully.

We distinguish between two types of availability analyses: first, analyses used to predict long-term performance from installation (time $t=0$) until over some period of interest such as early life; second, analyses used to predict short-term performance as the farm is operating (from some time $t>0$) and on the basis of the experience accumulated up until this point in time.

Let $t=0$ be the time the farm starts operating. Assuming that all turbines at time $t=0$ are in a perfect operating condition, i.e. $X_i(0)=m$ for $i=1,2,\dots,n$, we are interested in the *expected* performance of the system at time t , i.e. in the *expected* point availability-informed capability of the farm at time t from time 0

$$E_0[C(t)] = \frac{\sum_{i=1}^n \sum_{j=1}^m P_j \Pr[X_i(t)=j | X_i(0)=m]}{nP_1} = \frac{E_0[OP(t)]}{nP_1} \quad (7)$$

where P_j is the maximum output power of a turbine at state j and $E_0[OP(t)]$ is the expected maximum output power of the farm at time t from time 0 given the technical availability of the turbines. Such predictions are usually generated at a pre-construction stage, before the system is released into operation. In this case availability is assessed on the basis of generic data and/or engineering judgement rather than observations coming from the particular system.

Operators, on the other hand, are mostly interested in measuring the current performance of a system and producing short-term performance predictions on the basis of observations. Let $s>0$ be the present time; we are interested in forecasting performance from time s to time t in the near future on the basis of the experience accumulated over $(0,s)$. In this case the indicator of interest is the *expected* point availability-informed capability of the farm at time t from time s , for $0<s<t$, which is equal to

$$E_s[C(t)] = \frac{\sum_{i=1}^n \sum_{j=1}^m P_j \Pr[X_i(t)=j | X_i(s), X_i(s-1), \dots, X_i(0)]}{nP_1} = \frac{E_s[OP(t)]}{nP_1} \quad (8)$$

In this case availability measurements are generated on the basis of observations collected from the operation of the system, and, if available, usually require the analysis of large datasets.

Figure 2(a) is a visual display of the *expected* availability-informed capability calculated from time 0, used to predict system performance over some interval. Figure 2(b) portrays the one-step ahead predictions of the *expected* availability-informed capability. Such graphical displays are useful for monitoring performance.

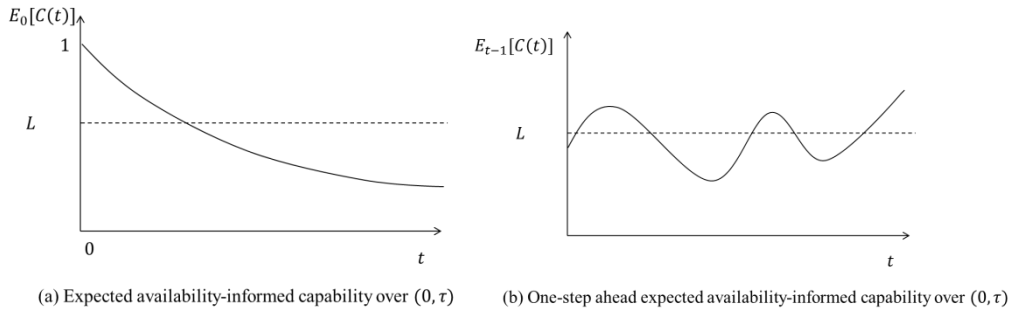


Figure 2: Performance of an offshore wind farm

Indicators (7) and (8) describe performance in terms of power output. The advantage of this is twofold: first, technical performance is integrated with producibility, to result in an indicator that can be used meaningfully within a financial context; second, the effect of intermediate operational states on system performance is defined in terms of reduced output. As a result, farm performance as described in (6) avoids the pitfalls of using a binary state-space to describe system functionality.

Of course, the power produced by a wind farm depends on the wind resource available on site. To account for this Definition (6) needs to integrate wind power curves that describe the output characteristics of the turbines and wind speed profiles representative of the area to predict energy yield. Generalising this definition to take into account the stochastic nature of wind will result in a more accurate prediction of performance. Moreover, in practice periods of low speed are often used to undertake planned maintenance and other actions that require that turbines become disconnected. Therefore, from a financial perspective, it is often of interest to assess system availability during periods of productive wind speeds only. Through the use of power curves, availability calculations can be focused on periods with particular wind speed profiles.

Modelling Uncertainty

Offshore wind farm power generation is subject to much uncertainty. This uncertainty impacts on the failure and repair processes of offshore wind systems, which in turn determine the availability levels achieved, and the wind resource. Incorporating the sources of uncertainty when predicting the performance of a wind farm, and quantifying the impact of uncertainty on the results of the analysis, is essential in evaluating performance risk.

In general, uncertainties can be categorised into aleatory and epistemic. Aleatory uncertainties relate to the natural randomness characterising both the system and environment. As an example, the wind profile on site varies over the years; wind turbines can behave differently inducing randomness in the failure and repair processes and the generated output at some wind speed. Aleatory uncertainties are irreducible, and the best one can do is describing them appropriately. Epistemic uncertainties, on the other hand,

relate to the limitations of knowledge about the system and the environment. For instance, limited experience with a particular turbine design introduces uncertainty in the estimation of the parameters of reliability models. The main characteristic of epistemic uncertainties is that they can be reduced by better information.

When it comes to offshore wind farms, in particular, epistemic uncertainties can be significant. First, offshore wind systems are newly designed systems operating in new environments; lack of knowledge of the system and environment is considerable and can have important implications in the reliability analysis, and availability modelling as an extension. This source of uncertainty can be modulated through e.g. additional testing. Second, there is lack of data on the operation and maintenance (O&M) of offshore wind farms, especially during the warranty period of the turbines. During this period, turbine manufacturers collect O&M data, however this is not accessible to the public due to confidentiality issues. This source of uncertainty can be modulated through e.g. the accumulation of operational experience from similar systems.

Aleatory uncertainty in system behaviour is modelled by using stochastic processes $\{X(t), t \geq 0\}$. Systems like e.g. wind turbines are repairable systems, and the behaviour of process $\{X(t), t \geq 0\}$ is driven by the failure and repair parameters of the model, denoted with Θ . Epistemic uncertainty relates to the values that parameters Θ take. Therefore, epistemic uncertainty is incorporated in the model by assigning a joint uncertainty distribution on the model parameters, $f(\Theta)$.

Modelling epistemic uncertainty is important for a number of reasons. First, the effect of this type of uncertainty can have significant impact on assessing the performance of a wind farm. Lack of knowledge affects all turbines across a farm in a similar manner. Since wind farm performance is calculated by aggregating the performance of individual turbines, not representing uncertainty may lead to significant over- or under- estimations of wind farm availability. Second, modelling the sources of epistemic uncertainty allows decision-makers to identify the main drivers of risk. This may provide new insights into the ways in which uncertainties may be mitigated and allow for the quantification of the effect of reducing uncertainties.

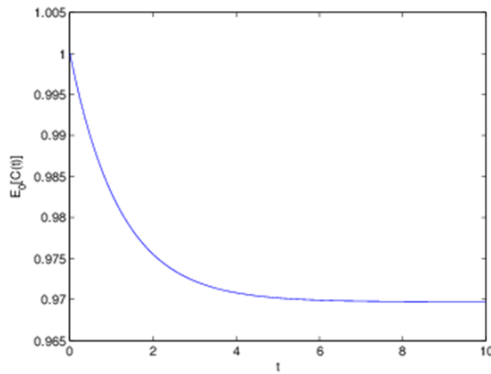
Illustrative Example

In this section we use a simple example to illustrate the incorporation of epistemic uncertainty in wind farm performance estimation. Consider a wind farm comprising of 20 identical wind turbines that is at a pre-construction stage. The interest lies in predicting the performance of the wind farm over its early life, assumed to be over (0,10).

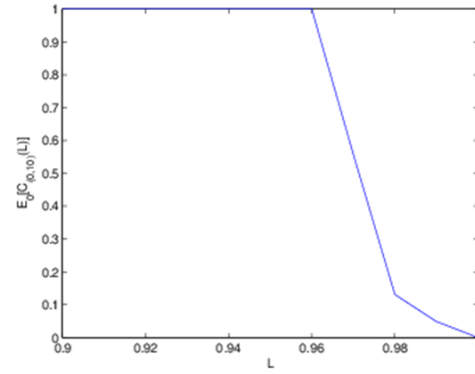
When we model the future operation of the farm, we suppose that turbines will be subject only to corrective maintenance, and that after maintenance the failed turbine is restored to an as good as new condition immediately. Moreover, we assume that turbines will be either operating or not operating. A turbine's failure rate is constant and equal to $\lambda=0.025$

(occurrences per time unit) and has repair duration of $\frac{1}{\mu}=0.8$ time units. This is a very simple setting, as our example is only a ‘toy-model’ used to demonstrate the effect of modelling uncertainty on performance assessments. The same approach can be extended to more sophisticated models.

Assuming that the maximum theoretical power output from a wind turbine is 5KW per unit of time, the expected average availability-informed farm capability $E_0[C_{(0,10)}]$ is equal to 97.3%. Figure 3(a) portrays the expected point availability-informed farm capability from time 0. One can see that the farm is expected to reach an acceptable level of capability equal to 97%.



(a) Expected availability-informed capability from time 0



(a) Expected level- availability-informed capability over (0,10)

Figure 3: Expected performance of example offshore wind farm measured from time 0

The cumulative maximum power output over period (0,10) is estimated to be equal to 973.4KW. Figure 3(b) shows that the farm is expected to reach comfortably capability levels beyond approximately 96%; however, the farm is expected to be unable to achieve much better performance than this, with capability expected to be above approximately 97% for less than 60% of the time and above 98% for less than 15% of the time.

Given the limited experience existing on offshore systems, the failure behaviour of turbines is a source of risk. There is a change that wind turbine reliability is much worse than expected. In particular, suppose that the turbine failure rate is uncertain and can take any value between 0.01 and 0.04. This is incorporated in the model by assuming that the turbine failure rate is a variable with a uniform uncertainty distribution, i.e. $\lambda \sim U(0.01, 0.04)$. We use Monte Carlo simulation to calculate uncertainty bounds on the estimates of interest. Figures 4(a) and 4(b) portray the results of the analysis as before, with the corresponding uncertainty bounds. The lower bound of the expected capability reaches levels beyond 97%, implying that there is a chance that an acceptable performance of 97% capability may not be achieved in the long-term.

The 95% uncertainty interval for the cumulative maximum power output over period (0,10) is (958.7,987.3)KW, implying that there is chance that the farm output is as low as 956KW. Risk-averse decision-makers might adopt conservative estimates and use the lower bound of the uncertainty interval to inform meaningful assessments.

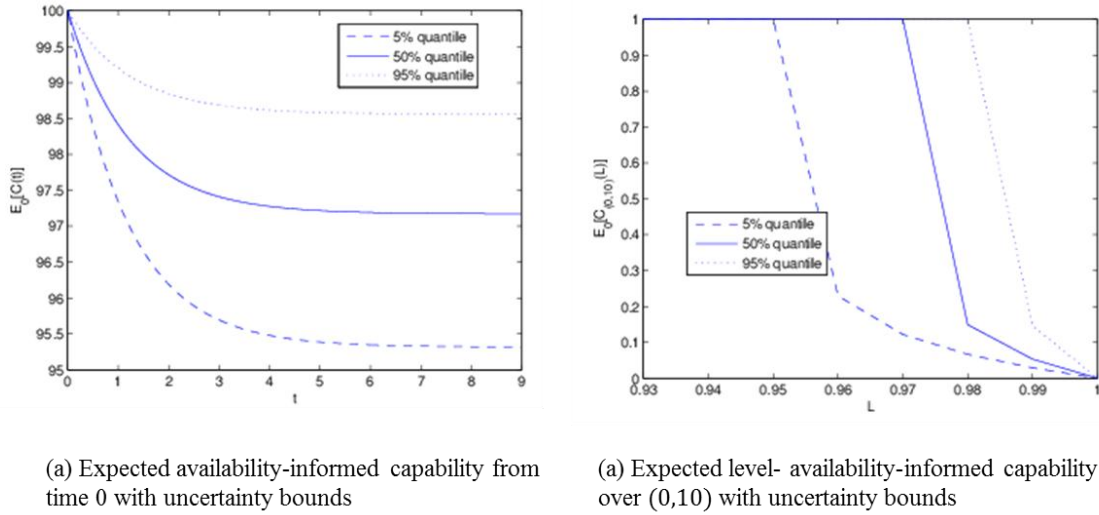


Figure 4: Uncertainty analysis on example wind farm performance predictions based on 100 simulation runs

Suppose that the farm has started operating and that current time is $t > 0$. In practice, short-term predictions of wind farm performance for the near future $(t, t+\tau)$, for some $\tau > 0$, are useful as they relate to the power produced by the farm over the next short time window. This information is useful when it comes to making decisions regarding e.g. energy transactions to and from the grid. Short-term predictions are produced on the basis of observations, accumulated until up to time t , as farm performance is monitored by e.g. operators.

Assume that the latest observation of farm performance is at time t . From an operational perspective, it is interesting to know the expected availability informed capability over interval $(t, t+\tau)$, as well as the expected proportion of time farm capability is above some level L , viz.

However, it may be useful to obtain such short term estimates at a pre-construction stage, i.e. at $t = 0$, without actually monitoring, but forecasting, the performance of the farm until time t , i.e. estimate expectation

$$E_0(E_t[C_{(t,t+\tau)}(L)]) = E_0\left(\frac{1}{\tau} \int_t^{t+\tau} 1\{E_t[C(u) > L] du\}\right)$$

This can be achieved by considering different possible ‘performances’ of the farm until time t . To obtain such estimates, one needs to simulate failure and repair processes with uncertain parameters (as before, uncertainty distributions are assigned on the model parameters). The produced indicator is subject to both aleatory uncertainty (farm observations up until time t differ because of natural variability captured by the stochastic

processes) and epistemic uncertainty (farm observations up until time t differ because of lack of knowledge of the repair/failure parameters). Figure 5 illustrates the expected performance of the farm assuming that observations on capability become available every 1 time unit ($\tau = 1$). The deeps in Figure 5(a) imply that the farm does not produce electricity at this point in time. Figure 5(b) is a visual display of the level-capability for some assumed time window of interest towards the middle of early life (5,6).

$$E_t[C_{(t,t+\tau)}(L)] = \frac{1}{\tau} \int_t^{t+\tau} 1(E_t[C(u) > L]) du$$

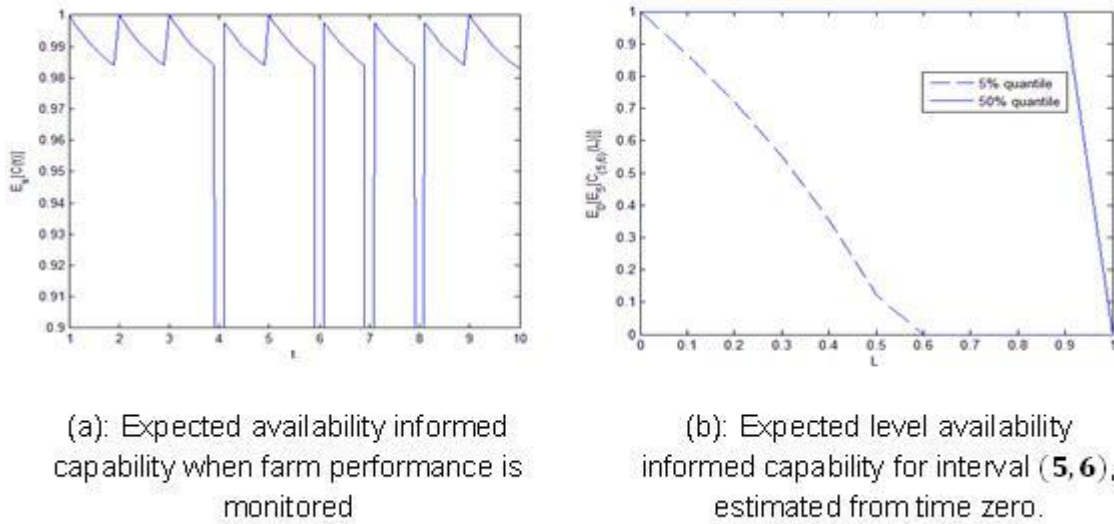


Figure 5: Uncertainty analysis on example wind farm performance predictions based on 50 simulation runs, assuming $\tau = 1$.

Summary & Conclusion

The objective of this paper has been twofold: to define a meaningful availability indicator and to highlight the important of uncertainty analysis in availability analyses.

Predictions of availability are key in assessing the performance of an offshore wind project over some operating interval such as early life. Nevertheless, there is inconsistency in the definition of availability found in the literature and used in practice. This may be problematic for both the calculation and interpretation of availability estimates. Here we discuss the sources of ambiguity and suggest an availability-informed performance indicator to address these. We define the availability-informed capability of a wind farm as the proportion of the maximum power output, given technical performance, over the installed power. This indicator describes performance in terms of power output. This is an important feature, as it captures the effect of partially operating turbines on the overall output and can be clearly associated to yield.

Offshore wind farms in particular are considered high risk. This is because they are novel systems and there is limited operating experience available. Due to this lack of knowledge about the system and its operating environment, there is epistemic uncertainty that needs to be incorporated in performance predictions. We illustrate this point by using a toy-model, but a similar approach can be extended to more complex models. We express uncertainty on the turbine failure rate by using a probability distribution and performing Monte Carlo simulations to explore how this uncertainty is propagated on performance predictions. It can be seen that there is difference between the point estimates and the lower bounds obtained from incorporating uncertainty. This difference could make a difference for risk-averse decision-makers, in particular.

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The combined effect of Scale and Non-stationary Conditions on Predictive Health Monitoring Procedures: A Case of Wind Turbine

Idriss El-Thalji¹, Erkki Jantunen¹

Industrial Systems, VTT Technical Research Centre of Finland, Espoo 02044,
FINLAND

idriss.el-thalji@vtt.fi, erkki.jantunen@vtt.fi

Abstract

The condition monitoring and predictive health practices have become significantly important part of offshore wind farms in order to cut down operation and maintenance costs. Machine dynamics, machine rotational speed and sampling procedures are three significant features with the stochastic nature and together increase the complexity of predictive health monitoring (PHM) procedures. The purpose of the paper is to demonstrate; first, the influence of scale and environmental loading conditions on the reliability of the rotating components of wind energy system; second, their influences on PHM procedures. The case study method has been utilized; the target of analysis is the wind turbine gearbox (WTG) as a component that is facing operational challenges due to its scale and environmental disturbances. This paper result in first explores scaled-up design features and their associated failure modes. Second, it shows the effects of these features as interference, defect noises and others issues on whole monitoring procedures. Wind turbine as a scaled-up system has critical points where it's technical specifications, components, interfaces, functions could require careful modifications. The effectiveness of PHM system is significantly affected by those critical points.

Keywords – Wind farm, Predictive health monitoring, Scaled-up design, Non-stationary loading, Wear

Introduction

The condition monitoring and predictive health practices have become significantly important part of offshore wind farms in order to cut down operation and maintenance costs. The challenge is to enable Condition Based Maintenance (CBM) strategy to be implemented in order to provide maintenance decisions and services at the right time i.e. maintenance is performed when it is needed and not too early and in vain and not too late i.e. causing breakdown and downtime. Nowadays monitoring and predictive practices within wind power applications are purely based on deterministic models even when it is known that the loading and operating conditions are stochastic by nature, furthermore, the wear and fracture growth are highly progressive than in other rotating machinery like paper mills, hydropower turbines and aircraft turbines. Tavner et al. (2006) highlighted that the configuration, technology and size of wind turbines (from 100 kW up to 2.5 MW) have been changing rapidly over last few years. Generally, there are two paradigm trends within wind turbine applications; scaling up and installing in harsher sites. Identifying the influence of these two trends is significantly important for failure processes and their PHM procedures. The figure 1 below illustrates the

main wind turbine concepts. Mainly, there are four main availability-based concepts behind the current industrial innovation and technology development; (1) scale up swept area, (2) enhance the capacity factor of rotor, (3) accelerate the wind speed in front of rotor; and (4) install wind turbine in high wind available sites such as offshore, deep offshore and cold climate regions.

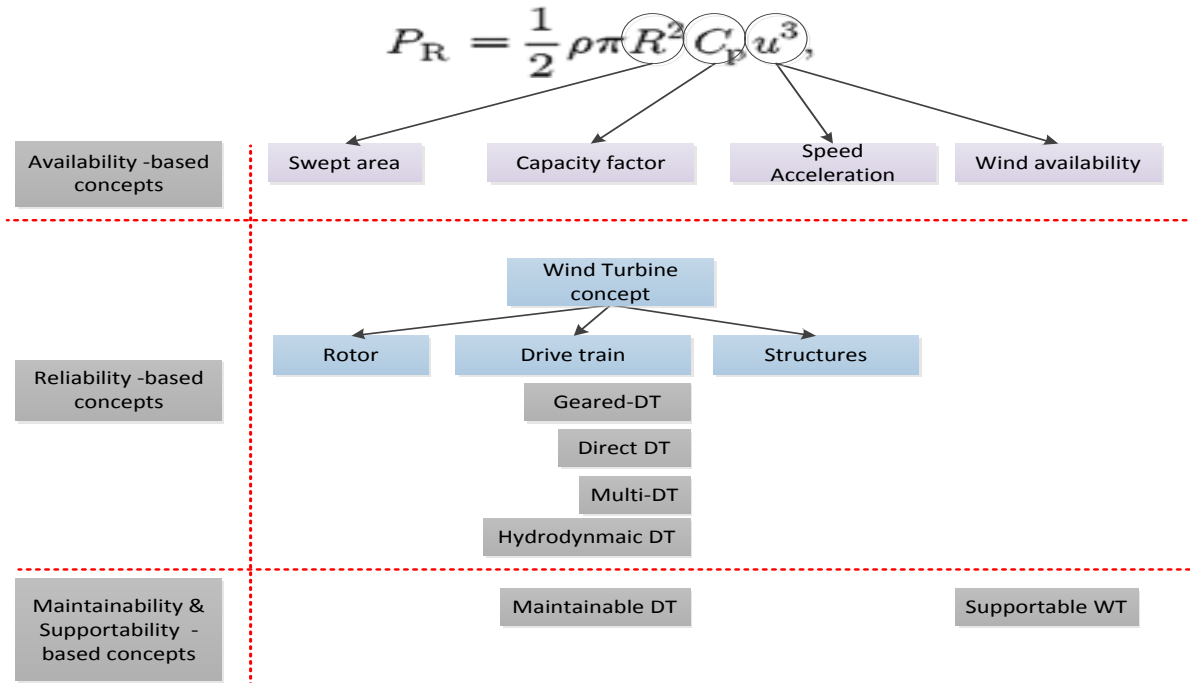


Figure 1, main wind turbine and drive-train concepts

In principle, all wind turbine components are subject to damage and have a limited lifetime. However, Eren et al. (2011) illustrate that electrical systems have a high failure rate, while mechanical systems (i.e. gearbox) have high repair downtimes, and aerodynamic systems (i.e. rotor) require frequent inspections. These three problematic issues are related to reliability, maintainability and supportability respectively and therefore it highlights the definition of dependability as collective term of these three terms. In this sense, there are a number of hypotheses regarding the root-cause of real problems (failures, downtimes, frequent inspections, etc.) as follows; (1) Scale, Tavner et al. (2008) discussed the reliability figures of three size ranges of wind turbines (i.e. small size (<500kW), medium size (>500kW and <700kW), large size (>700kW)). The paper present the figures based on the database of Schleswig Hostein LandWirtschaftskammer (LWK). It was observed that failure frequency rate per year in average is around; 0.1 for small size, 0.2 for medium size and 0.5 for large size. (2) Loading patterns and Operating conditions: some studies illustrate the effect of environmental disturbances on the failure rate of specific wind turbine components. Tavner et al. (2010) observed statistically cross-correlation (55-75% on monthly incidents) between failure frequencies and weather patterns of the three studied wind farm locations.

A previous survey study (Tavner et al. (2008)) expresses holistically the failure distributions for all considered wind turbine concepts but there is no information about the predominant cause behind the increasing of failure rate; whether is it due to size or operating conditions. For example, Tavner et al. (2008) illustrated some of issues related to scaling-up process of wind turbine generators; number of coils, difficulties to seal the windings of large generator

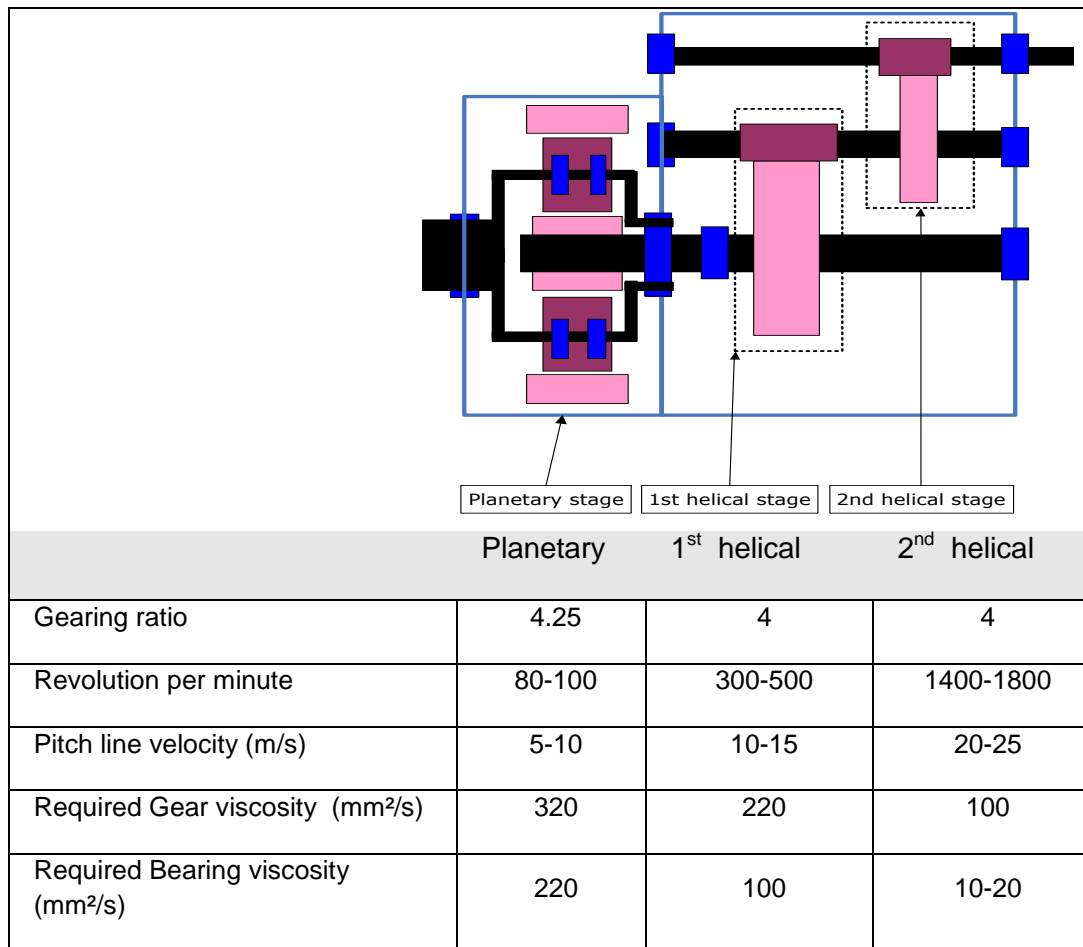
from its environment, and insufficient standardization of large size generator machines. In general, Gegner (2011) stated that larger size roller bearings with extended line contacts operating typically at low to moderate Hertzian pressure are most susceptible to have severe surface loading. In wind energy application context, it is well known that the wear of rolling bearings share the largest portion of failures (71 % according to Swedish database (Horste and El-Thalji 2011)), however, the causes and dominant wear processes are still under investigation. Unfortunately, the failure databases have a number of ill-classified issues that make it hard to say what the main problem of current gearboxes is; is the failure due to components, their technical specifications, or in their interfaces? Therefore, there is a need to have a detailed case study of specific wind turbine gearbox and its components in order to extract what are main scaled-up design features that affect overall system reliability.

The wind turbine drive train is defined as the mechanical combination of slow-speed and high-speed system. The statement covers planetary gearing, intermediate-speed gearing and high-speed gearing stages. From condition monitoring point of view, this combination could complicate the monitoring procedures and bring a number of limitations. For example, Jamaludin et al. (2001) listed four limitations for slow speed machinery: (1) the conventional vibration monitoring systems that employ accelerometers are not suitable for such low-speed frequency analysis; (2) it involves overcoming inherent low frequency instrument noise problems and low frequency roll-off limitations of the charge amplifier; (3) most sensors have roll-off filters that affect the magnitude of signals detected within roll-off frequency range; (4) the allocation of sensors could bring some rocking effects and noise at very low frequencies. Also Bartelmus & Zimroz (2009) have discussed the difficulties of monitoring of planetary gear, and the monitoring difficulties of a multistage gearbox due to the interaction between components in a multistage gearbox system and external components (i.e. electric generator, damping, coupling, etc.) to gearbox. Based on the above discussion we can argue that scaled-up design features have a number of effects on PHM within wind turbine application starting from measuring, sampling, signal analysis, diagnostic and prognostic tasks. The paper demonstrates these effects and technical requirements for an effective PHM procedure, in order to enable scaled-up systems to run under non-stationary conditions.

Case Empirical Findings and Discussions

The wind turbine gearbox has been purposefully selected to present the effect of scaling-up process on potential failure modes and associated monitoring procedures. Dinner (2008) presents the main trends of wind turbine drive trains and related gearboxes. One of the most installed turbine types is that of 660kW with three stages gearbox (i.e. one planetary stage and two helical stages); please see the Table 1 below. Therefore, the case study is limited to the wind turbine gearbox and its wear failure mode as the most critical issue in current wind turbine applications. This assumption is not to say that wear is the only failure mode rather than to express that the wear mode is a predominant one among other modes. Moreover, the authors try to study the most critical mode separately as a starting point under this stage of research; however, the forthcoming studies shall cover also other modes and their interaction with the wear mode.

Table 1, WTG configuration and technical specifications (for 660kW turbine size)



On the basis of table 1, some technical facts about scaled-up gearbox are extracted as follows:

- Architecture: The chosen gearbox has three stages; each stage has a range of rotating speeds. Thus, it involves slow speed components and high-speed components.
- Functions: The gearbox has a number of specified functions; however, the scaled-up gearbox could involve more functions or supportive functions. For example, the transmission or gearing-up function for the first stage shall have an additional function to carry-on high load, and in some situation absorbing impact loads.
- Components: Sizes, types and numbers of components are main characteristics of scaled-up systems.
- Interfaces: Sizes, types and numbers of interfaces.
- Technical specifications: For both components and interfaces, it might be that the scaled-up system utilises the same type as a smaller one would, but in reality it might require totally different technical specification.

The case study tries to answer three main questions; what are the main features of scaling-up design process, how do these features influence the failure processes, and how do these features complicate the monitoring procedures?

What are main scaled-up design features?

The section illustrates the main scaled-up design features of the studied case. The illustrated features classified into six categories; functions, components, interfaces, specifications, environmental conditions and overall architecture of the studied system.

Functions: Yagi & Ninoyu (2008) stated that the bearings on the planetary shaft, intermediate-speed and high-speed shafts all see a complex series of loads consisting of both high axial and radial loads. However, low-speed shaft bearing have to feature greater load carrying capacity and also smooth high-speed operations. (ISO81400-4 2005) indicate that scaling up the system increase the impact torque loads as well as the idling, parking and transient operations' loads (i.e. braking, cut-in, cut-out, generator shifts and blade pitch operations). More idling and parking loads means more false brinelling, fretting corrosion and corrosion on gear teeth, splines, rolling elements and raceways. Load sharing between rolling elements are another issue due to scaling-up process. Load sharing between gear teeth in which no tooth is loaded more than severally than any other; unfortunately, this is not always the case for scaled-up systems. Bearing arrangements could vary from location to another with same gearbox. It could be paired arrangement (i.e. same bearing types at the same location, their radial capacities are complement and their axial capacities are opposite), combined arrangement (i.e. two different bearing types at the same location to fulfil separate functions), tandem arrangement (i.e. same bearing types at the same location, their radial and axial capacities are complement), and double row bearing arrangement. Housing has function to ensure that all gear sets and their bearings contact are correctly configured.

Components: In order to allocate these functions, a number of components are scaled up in terms of size and quantity. For example number of gearing stage, gear set sizes, number of supported bearings, and number of rollers of bearings.

Interfaces: The interfaces are also affected by current design, for example, the current used cage is not allowing the size and quantity modifications due to the cage strength issue. Therefore, the trend is to use separator style cage which avoid a major drawback of a full complement bearing. Lubricant is a tribological interface that lubricates, cools, cleans and carries out debris within and from gearbox. Housing fits -in such scaled-up system- makes the tight fits are necessary to prevent damage to the bearing or housing.

Specifications: The weight and rotation of the rotor applies a load to the main shaft bearings. Therefore, in the standards (ISO81400-4 2005) all requirement for the geometric configurations of gearbox elements (i.e. gears, shafts, bearings, seals, mountings and housings) are specified, that includes; lengths, widths, heights, distances between shaft centres, lengths of shaft extensions, angles of shaft tilt and offsets, gear housing split plane, internal clearances, and other features. For example, Yagi & Ninoyu (2008) presented the relationship between rated output in MW and main bearing size. The relationship is almost linear, for instance, 1MW turbine size needs around 400 mm bearing size, and 2 MW turbines need 700mm bearing size. Surface imperfections are another category of specification that always attached to scaled-up systems. According to (ISO81400-4 2005) it is highlighted that the roughness profile of gears and bearings is still dominated by the texture generated in the finishing process, however, those imperfections produce high local stresses at roughness peaks, in which they cause micro-pitting, surface distress, scuffing and wear. Scaled-up system requires greater rating life specifications which is significantly

important to achieve durable design life of 20 years. For example, HSS has estimated rating life approximate 30,000 Hours, while LSS around 100,000 hours. Scaled-up system may have greater and different contact stresses on each shaft type. The aspect ratio is an indicator of how sensitive a gear set is to misalignment. Due to scaling-up process the aspect ratio could be scaled up or shall have different limits, in particular, to be suitable for self-aligning systems. The gear profile shift also scaled up in order to avoid undercut, however that increase the sliding actions. The scaling-up process makes gear involute profile modification to become complicated, since it shall minimise the detrimental effects of tooth deflections, assembly tolerances and tooth variations in which are related to increase the load capacity and reduce noise. Besides scaling-up issue, the load variability with wind turbine application enforces the designer to consider different loads patterns and not only one load pattern. For bearings, the internal clearances are one of most important specification in order to accommodate heavy interference fits and temperature differences. The radial clearance of low speed shaft bearing is directly affecting the misalignment of the gear mesh. Interface characteristics; the viscosity degree that in use is 320 mm²/s, based on the estimation of required viscosity for slowest pitch line speed. In this case, the viscosity degree is suitable for planetary gearing stage. However, the gaps between the required viscosity degrees for HSS and LSS cannot be optimised. In this sense, having high viscosity degree for HSS and its bearings is quite problematic in terms of having starvation events and abrasion actions. Furthermore, operating temperatures are important for viscosity ratio and lubricant supply process. The problem associated to scaling-up process is the differentiation of required operating temperature may highly vary, for example, planet gear and HSS gears, the same goes to bearings as well. Another issue related to lubricant as interface is cleanliness. Cleanliness is become sever issue with scaled-up system due to a number of things, seals, clearances and number of dirt and debris sources. Moreover, it relates also to filtering process; filter capacity and resolution. Operational characteristics of gearbox elements are highly important in wind energy application.

Environmental conditions: extreme torques could impose the wind turbine, where higher torque level applied, greater number of occurrences. Furthermore, ambient temperature, humidity, extent of exposure to direct sunlight, etc. are considered as environmental interfaces. Bossanyi et al. (2008) conclude that peak loads and duty cycle have impact on gearbox dynamics and its lifetime.

Architecture: Scaling-up process has direct impact of machine architecture as a sum of whole described features. Yagi & Ninoyu (2008) present main three shaft configurations; one-bearing support, two-bearing support and integrated bearing support. These three types have different number of bearings, type of bearing (for example, first one use cylindrical roller bearing and second use double-row tapered roller bearings), self-aligning mechanism (fixed rib, guide ring, etc.) and lubrication type (for example, third one uses grease lubrication).

What are main effects of scaled-up features on system deterioration?

Previous illustrated scaled-up design features (i.e. functions, components, interfaces, specifications and architecture) are in total expected to cause a number of real failure and operational issues as follows; (1) ineffective seals, (2) contaminated lubrication with debris and foreign particles, (3) improper lubrication or lubrication which lost its lubricating

properties, (4) unable to withstand the vibration while stationary (5) sliding under heavy axial loading and inadequate lubrication, (6) bearing seatings out of alignment, (7) interference fit on cylindrical seating too heavy.

The empirical findings of studied case show some of these expected failure modes for both bearings and gear sets, please see Table 2.

Table 2, wind turbine gear and bearing failure modes



Inner ring raceway



Spalling & flaking caused by inadequate lubrication



Mild wear caused by parked-state



housing Scoring caused by heavy loaded bearings



Smearing, cylindrical rollers caused by ineffective lubrication



Inner Ring Raceway loads are excessive



Wear in planet wheel



Fracture of Sun wheel



Teeth fracture, HSS-pinion

These wear processes could be explained based on Jantunen (2006) illustration where he described a simplified wear process scenario for a rolling bearing based on a number of previous research work and experimental tests. The wear begins with fatigue. Later, wear particles become a part of the lubricant and the oil circulation carries them around that

introduce abrasive and adhesive wear and larger geometrical imperfections are initiated. also, Halme & Andersson (2009) described the whole wear processes from micro-pitting up to spalling. The low-speed shaft bearing (LSS) and the high-speed shaft bearing (HSS) both have slightly different failure modes, LSS bearing is affected by high impact loads rather than adhesive and abrasive impact due to poor lubrication as is the case with HSS bearing. Imperfections in roller diameter, inner and outer race waviness and roughness have clear impact. Sunnersjö (1985) studied and highlighted the impact of geometrical imperfections on the vibration of rolling element bearings. Halme & Andersson (2009) described four types of tribological contacts and their influences on diagnostics of defect. Moreover, they describe the starvation events and how it occurs. Farcas & Gafitanu (1999) illustrated the influence of temperature on the bearing lifetime for grease-lubricated bearings, in particular, the lubricant viscosity. Dwyer-Jones (1999) described the abrasive action, distance of particle slides in the ball bearing contact. Fitzsimmons & Clevenger (1975) analyse the influence of contamination on bearing wear. Coultate et al. (2009) conclude that depending on design features, the flexing the structure (i.e. housing and carrier) affects the misalignment at the contacting tooth and roller surfaces. Thus, in result, the misalignment will produce several stress distributions and hence reduce component lifetime. Based on the above, we can argue that machinery health measurements for large scaled-up system under non-stationary loading and operating conditions produces non-cyclic signals, in which the detection process become more complicated than normal ones.

What are main effects of scaled-up features on PHM procedures?

The previous real effects of scaled-up design features clarify the impact of these features also on monitoring procedures. Mainly, due to their effects on increasing the background noise, defect noise and interferences are much complicated compare to traditional simple applications. Culita et al. (2007) illustrate the general vibration model (please see figure 2). The model describe the main generated signal groups when a mechanical system is running; natural oscillations, interference signals (due to interactions of different elements), and defect noise. Altogether with environmental (background) noise generates what called 'crude vibrations' in which measured by sensors (connected to transducer) and converted into electrical signals. First point, this model are useful to describe the detection procedures, however, monitoring procedure proceed to analyse the measured signals using signal processing techniques and algorithms, later diagnostic information is extracted from these processed signals using classification and other intelligent techniques. Finally, the diagnosed information provides the extension for prognosis technique to process these information sets in order to make a supportive decision. The worth of extending the general vibration model to cover whole predictive health monitoring procedures is that, in fact, in each of those steps the signals, data, information are distorted somehow. For example, transducer can distort the crude vibration, the Fast Fourier Transformer (FFT) analysis has limitation to deal with distorted signals (due to discontinuity), and however it distorted the frequency domain with a number of undesired harmonies. Furthermore, the diagnostic and prognostic could be underestimate, overestimate, and even neglect the extracted information, thus another type of information distortion is involved. In total, the predictive health monitoring shall be viewed as a chain of procedures. Second point, the model illustrate the effect of scaled-up features on natural oscillation, interferences, defect noise, and environmental noise, however, condition monitoring procedures begin to measure at the point of what the model call it 'Crude vibration', which is a complicated combination of all those vibrations and noises.

Actually, the issue of inaccuracies of condition monitoring have been discussed by Jin & Embury (2003) where two different types of inaccuracy illustrated; (1) the incompleteness of the results, and (2) the need to avoid accessing certain systems during certain periods of time, and delays in query processing. However, the case of wind turbine shows more inaccuracies -in the extension procedures- that might impact the whole PHM procedure chain.

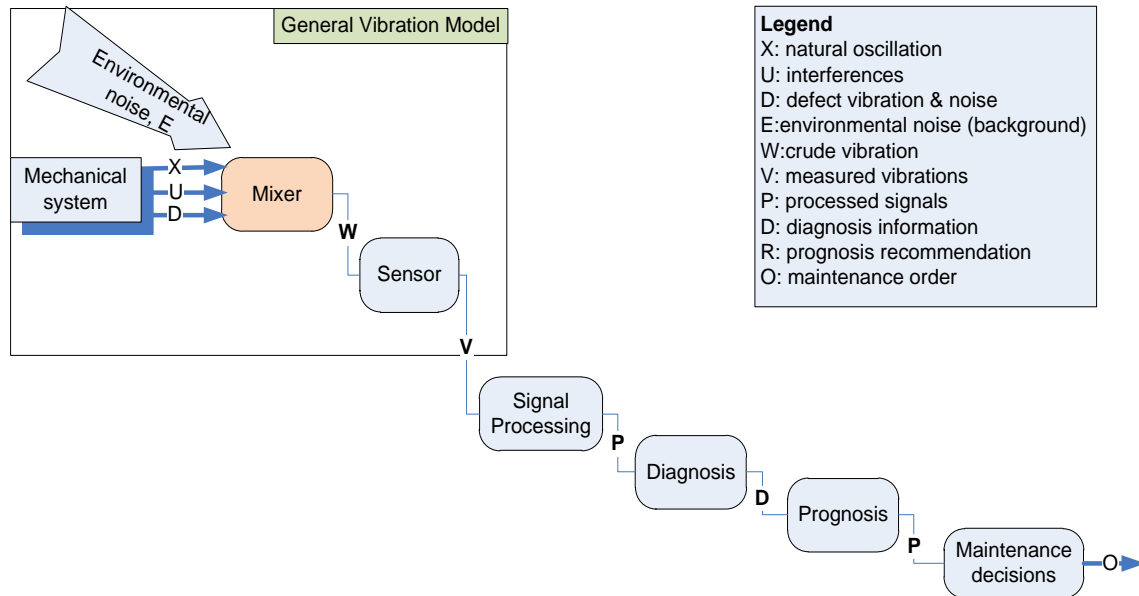


Figure 2, general vibration model and extended model

Therefore, in the following points, the effects of scaled-up features on PHM procedure chain and crude vibration combination are discussed.

Measurement and sampling techniques: The condition monitoring sensors that are required for WTG have to cover different frequency ranges. For example, in a WTG the rotor shaft rotates with speed around 20 m/s, the low speed shaft with 80-100 m/s, the intermediate shaft with 400-500 m/s and the high-speed shaft with 1400-1800 m/s.

Sensors allocation and related effectiveness; Sensors are allocated far from defect sources, and therefore the defect impact might be damped before it reaches the allocated sensor. Transfer channels and remoteness generates another types of technical and operational limitations.

Sampling procedures: sampling procedures; these procedures are automated in a deterministic way in terms of frequency and interval length, so they may miss the defective events which are not covered by the sample interval, or have insufficient information due to short sampling interval.

Signal analysis and detection techniques: The basic assumption of signal analysis technique is based on the continuous nature and the periodic repeatability of measured signals. Orhan et al. (2006) stated that the periods of vibrations are repeated at certain intervals, the frequencies of which depend on the bearing geometry features, the rotational velocity, and location of the defect(s). However, Randall (2004) stated that the frequencies of the cyclic impacts vary in a random manner, due to slip, varying speeds and varying load angle. In fact, a simple real case could represent the discontinuity and random repeating of signals

related to defects. Such simple real case could therefore provide unrealistic results when a traditional single analysis technique is implemented. Urbanek et al. (2011) investigate the speed tracking techniques in order to remove the speed fluctuations and smearing from the spectrum.

Diagnostic and prognostics techniques: wind turbines running on different speed ranges with frequent speed shifts depend on instantaneous wind speed changes, which complicate the amplitude detection of defective signals. Measured signals and detected symptoms are quite complicated in the case of WTG when compared to other sizes or stationary loading conditions. Extending the symptoms and prognostic analysis require more inputs and larger intelligent networks, in which also complicates the diagnosis and prognosis procedures.

Conclusions

The paper concludes that scaled-up design features contribute and produce mainly interferences and defect noises. Interferences and defect noises are significant parts of whole crude vibration that later will be measured and analysed as total output. The case empirical findings show that scaled-up design features also initiate several distributed faults as wear defects. Those distributed defects produces noises, however, they are not detectable at early stage. Thus, when those defects become 'big enough' and localised the condition monitoring techniques might detect them. Nowadays, the vibration variations in early stage are assumed to be due to operating conditions and, unfortunately, regarded as not significant. Scaled-up design features affect whole PHM procedure chain (as illustrated in figure 2) in form of interferences, noises, signal transfer, and signal processing, diagnosis and prognosis. Therefore, it is highly important to understand their related interferences and defect noises' patterns of each configuration in order to provide accurate and effective PHM system. Finally, the combined implication and influence of scaled-up design features and non-stationary conditions on system reliability and associated costs are illustrated in figure 3. It is clear that PHM procedure is seen as risk barrier of such scaled-up system running under non-stationary conditions to avoid costly failures, downtimes and production losses.

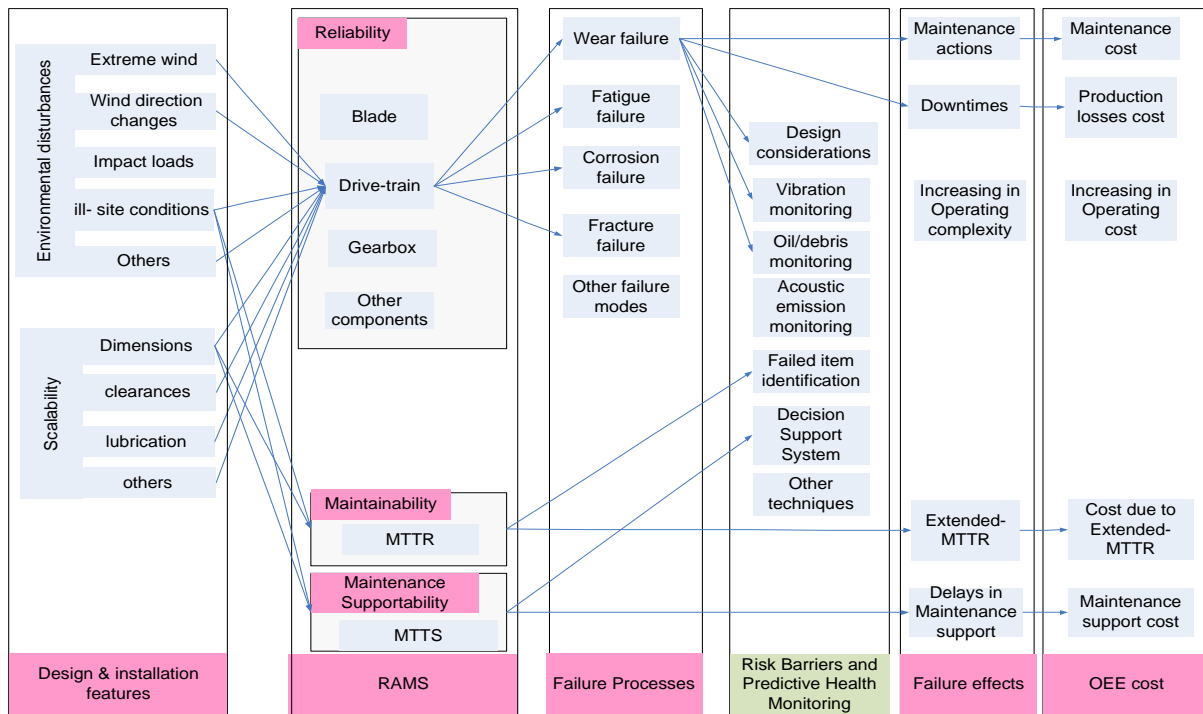


Figure 3, the influence chain diagram of environment and scale disturbances, wind turbine reliability, failure processes, PHM procedures and associated overall equipment effectiveness cost

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Wind Power Density Forecasting

Jooyoung Jeon¹, Patrick McSharry²

¹University of Strathclyde, UK

²University of Oxford, UK

jooyoung.jeon@strath.ac.uk

Abstract

Wind power is one of the fastest growing sources of renewable energy. The management of wind farms, electricity systems and maintenance scheduling can benefit greatly from the availability of estimates of the uncertainty in the power generated from each wind farm. Nevertheless, most research has focused on point forecasting of wind power. The time series of wind power and wind speed are characterised by high variability and regime-switching. Regime-switching techniques are applied to model distinct regimes in the level and volatility processes of wind speed time series. The probabilistic distributions of wind speed predictions are converted to wind power using conditional kernel density estimation. We evaluate the usefulness of the models for prediction from 1 to 72 hours ahead using a Spanish wind farm and four Greek wind farms.

Keywords: Wind Speed, Wind Power, Wind Energy, Predictive distribution, Conditional Kernel Density, Regime-switching, ARMA-GARCH

1. Introduction

Wind turbines are one of the fastest growing of the renewable energy technologies. Considering the cost of CO₂ emission, wind energy is considered as the second efficient renewable energy after nuclear power. Nevertheless, the fluctuating stream of wind and the complex nature of wind generation are still limiting factors in the utilisation of wind energy. The variability of generated wind power induces imbalance in distribution by grid companies and leads to a commitment to over- or under- production in the real-time market, which has to be compensated by alternative energy incurring penalties for wind generators. Unforeseen extreme wind gusts often severely damage wind turbines, which could have been prevented if accurate predictions for extreme events were available. Hence, accurate wind speed forecasting is a prerequisite for better utilisation of wind energy.

While point forecasting of wind speed has been predominant in this study, probabilistic forecasting is far less developed [1-5]. Without probabilistic predictions, the wind farm operators and transmission system operators are exposed to the risks involved in using forecasts for decision making about the scheduling of the production of unit commitment. In this context, probabilistic forecasting of wind power generation, which can be used together with existing point forecasting systems, is becoming crucial for risk management in technical

and financial decision making, as well as for the safe and efficient operation of the electricity transmission network. The study of probabilistic wind energy forecasting also has societal benefits because it can contribute towards the adoption of renewable energy through a reduced need for reserve margin, and because it can enable more efficient energy management that should result, in turn, in reduced reliance on power generation from fossil fuels. The results of the study will be of a great value in estimating and communicating prediction uncertainty and risks. The study of probabilistic wind energy forecasting is also timely because of the growing debate about the value and feasibility of wind generation as a source of renewable energy.

In terms of the forecast horizons in this paper, we produce density forecasts of wind speed and wind power for lead times from one to 72 hours ahead. For balancing purpose, due to the intermittency and non-dispatchable nature of wind energy, accurate short-term wind power forecasts from 15 minutes up to several days ahead are vital to transmission system operators, who maintain the balance between load and generation by scheduling spinning reserve and production from conventional plants. Accurate short-term wind power forecasts are also imperative for them to reduce the trading risk in spot and intraday balancing markets for supplemental reserve since one of the greatest uncertainties in electricity price originates from the intermittency and non-dispatchable nature of wind energy. For example, for the spot market of Nord Pool, which opens around midday for the following day from midnight to midnight, transmission system operators can develop optimal bidding strategies utilising wind power forecasts from 12 to 36 hours ahead. After the spot market closes, shorter horizons from one hour to 24 hours are relevant to optimal adjustment bidding in the intraday balancing market of Nord Pool. For independent wind power producers, the accuracy of short-term wind power forecasts is crucial for minimising the penalties for failing to meet the unit commitment for wind power generation, and very short-term forecast horizons from a few seconds to an hour are related to turbine active control in wind farms. Long-term horizons up to 7 days are useful for maintenance planning of wind turbines.

Probabilistic estimation of wind power intrinsically involves two key uncertainties: the uncertainty in wind speed and the stochastic nature of the power curve, which is the function relating wind speed to wind power. In [1], the uncertainty in the stochastic nature of the power curve is addressed using the combination of Monte-Carlo simulations and conditional kernel density estimation. In this paper, we develop an approach to wind speed density forecasting that accommodates the regime-switching characteristics of wind speed. We then convert the wind speed density forecast into a wind power density forecast via the explicit modelling of the stochastic relationship between wind speed and wind power [1]. The regime switching model brings advantages over the other probabilistic forecasting methods in the literature in that it can capture different dynamics in the periods of high variation wind and low variation wind.

The remainder of this paper is organised as follows: Section 2 describes the regime-switching models for density forecasts of wind speed and the conversion process to wind power density forecasts are described. Section 3 described the data we used empirical test and then evaluates the density forecasts from the various models we propose, and Section 4 provides a brief summary.

2. Modelling

Recent studies [6, 7] model the regime-switching patterns of wind speed. In [6], the westerly wind shows higher speeds than the easterly in the hourly averaged data sets at three meteorological towers in the US Pacific Northwest. They find the regime-switching model performs better than persistence, which uses the most recent observation at hand as a point forecast, and autoregressive time series models in terms of accuracy, calibration and sharpness criteria. In [7], a regime switching model, which comprises of a persistent model for a high wind and a regression based model for a low wind, is used, and state transitions with neural networks are found to be more accurate than that with logistic regressions. However, to identify such distinctive and straightforward regimes, to analyse how many regimes would be necessary, and to establish where the boundary of such regimes would be, involve extensive meteorological investigation. Furthermore, generalising the result to other locations is not easy and a choice of wrong regimes might well result in poor predictive performance [8]. In this paper, we model both the level and volatility in the univariate and multivariate models. We use k-means clustering algorithm to identify up to three regimes in wind speed. Up to three regimes seem to be sufficient considering the relevant wind literature. We are not aware of any other studies that have considered modelling the regime switching dynamics in the volatility process of wind speed time series so far.

A. Threshold ARMA-GARCH Modelling

A widely used class of models to capture the autocorrelation in the conditional mean and variance is the autoregressive moving average - autoregressive conditional heteroscedasticity model (ARMA-GARCH) and its various extensions. In [9], wind speed density predictions from an AR-GARCH model is produced. In [10], an AR-GARCH model with a Gamma distribution assumption is fitted to the daily wind speed measurements at Shearwater, Canada, and proves that heteroscedastic models outperform homoscedastic ones. In [11], an autoregressive model provides greater accuracy in the prediction of the conditional wind speed distribution than models based on an unconditional distribution such as Weibull and Rayleigh distributions, particularly for low wind speed systems. In this paper, we fit the following threshold ARMA(r,m)-GARCH(p,q) model with seasonal terms to our wind speed time series.

$$\sum_{j=1}^{S\varphi} \varphi_j(L) y_t = s(\boldsymbol{\mu}, t) + \zeta(L) \varepsilon_t, \quad (1)$$

$$\sum_{j=1}^{S\alpha} \alpha_j(L) \sigma_t^2 = s(\boldsymbol{\omega}, t) + \beta(L) \varepsilon_{t-i}^2, \quad (2)$$

$$\varepsilon_t = \sigma_t \eta_t, \quad (3)$$

where y_t is the wind speed observed at time t ; ε_t is an error term; η_t is Gaussian i.i.d. white noise; σ_t is the conditional standard deviation (volatility); L is the lag operator; $\alpha_j(L)$,

$\beta(L)$, $\phi(L)$ and $\zeta(L)$ are polynomial functions of the lag operator; S_ϕ and S_α are the numbers of regime-switching states in level and volatility, respectively; μ and ω are vectors of parameters; and the $s(\mu, t)$ and $s(\omega, t)$ are vectors of exogenous variables that have an effect on the mean and the volatility, respectively. In order to satisfy stationarity and invertibility conditions, all the roots of the autoregressive polynomial $\phi(L)$, all the roots of the moving average polynomial $\zeta(L)$ and all the roots of the sum of the GARCH polynomial $\alpha(L)$ and the ARCH polynomial $\beta(L)$ lie outside the unit circle.

Regarding the exogenous variables, we suggest the use of seasonality terms for both the mean and the volatility. The seasonal pattern is modelled as a linear function of Fourier series as in expression (4).

$$\begin{aligned} s(\mu, t) &= \mu_0 + \sum_{i=1}^{N_\mu} \left[\mu_{i,1} \sin\left(2i\pi \frac{h(t)}{24}\right) + \mu_{i,2} \cos\left(2i\pi \frac{h(t)}{24}\right) \right] \text{ and} \\ s(\omega, t) &= \omega_0 + \sum_{i=1}^{N_\omega} \left[\omega_{i,1} \sin\left(2i\pi \frac{h(t)}{24}\right) + \omega_{i,2} \cos\left(2i\pi \frac{h(t)}{24}\right) \right], \end{aligned} \quad (4)$$

where $h(t)$ is the hour of the day, and N_μ and N_ω are integers selected by the Schwarz's Bayesian Criterion (SBC). It is well known that wind speed and wind power generation are often characterised by diurnal and annual seasonal patterns [6, 12, 13]. The inclusion of Fourier series of hours of the day can help to capture conveniently the diurnal pattern of wind power. We do not attempt to model the annual seasonal cycle as our time series is not sufficiently long. In the literature, Fourier series is included to capture the asymmetric seasonal impact of wind speeds lower or higher than expected on both the conditional mean and conditional volatility [4]. On the other hand, models are fitted to the resulting residual series of the least square regression on trigonometric terms [6, 8]. Yet, in this approach, the periodic signal in the variance should be modelled separately. In this paper, the quadratic functions of Fourier series are directly plugged into the models both for the mean and the variance process, and their parameters are estimated together. The performance of the univariate autoregressive models is tested with a Gaussian distribution assumption for error terms. More distribution assumptions, such as Student t and skew t distributions, will be used in the future study.

B. Conditional Kernel Density

In [1], the nonlinear and stochastic dependency of wind power on wind speed is identified, and then this relationship is modelled using Monte-Carlo simulations and the conditional kernel density [14]. We define WP_t as a wind power observation at time t and WS_t as a wind speed observation at time t . Let $f(wp | ws)$ be the conditional density function of wind power given a wind speed, ws , which is a Monte-Carlo simulation result from the regime-switching ARMA-GARCH model in Section 2-A. The Rosenblatt CKD estimator [14, 15] of $f(wp | ws)$ can be re-written as

$$\hat{f}(wp | ws) = \frac{\sum_{t=1}^n K_{h_x}(WS_t - ws) K_{h_y}(WP_t - wp)}{\sum_{t=1}^n K_{h_x}(WS_t - ws)}, \quad (5)$$

where n is the sample size, and $K_h(\cdot) = K(\cdot/h)/h$ is a kernel function with bandwidth h . This formulation contains two bandwidths, h_{ws} and h_{wp} . They are scale parameters that control the amount of smoothing. The essential idea of the Rosenblatt CKD estimator is double kernel estimation, with kernel density estimation in the wp direction and kernel smoothing in the ws direction. For a given ws , the density function of WP_t at the value wp is constructed by applying kernel density estimation to the sample values of WP_t , with each WP_t value weighted in proportion to the proximity of the corresponding WS_t from the value ws . The Rosenblatt CKD converts one wind speed to a distribution of wind power. For each of Monte-Carlo simulations, we iterate this CKD conversion and then take the average of the wind power distributions, which is the wind power density transformed from the wind speed density.

3. Forecast Evaluation

A. Description on Data

In this paper, we use hourly observations of wind speed, wind direction and wind power at the Sotavento wind farm in Spain and four Greek wind farms in Crete: Aeolos, Rokas, Enteka and Iweco. The Spanish data is from a wind farm located at Sotavento, Galicia in the North Western part of Spain approximately 40 km from the coastline of the Atlantic Ocean. This site is located between 600 and 700 metres above sea level in semi-complex terrain. The wind is characterised by the global atmospheric circulation and local orographic complexity in Galicia. In winter, a strong and constant south-westerly wind regime prevails at the northeast of the peninsula because of the arrival of Atlantic ocean fronts. During summer, the anticyclone on the Azores Islands often creates north-easterly wind in Galicia. The wind farm has 24 wind turbines ranging from 600 KW to 1,320 KW and generates wind power up to 17.56 MW. Ten-minute observations of wind speed, direction and power generation are simultaneously recorded and averaged over each hour to yield a single hourly observation. Although data has been recorded since 1 July 2004, we chose a period only up to 11 March 2007 due to four weeks of missing data, thus returning 23,602 hourly observations of wind speed and direction. The wind speed, direction and power production data are rounded to the nearest 0.01 m/s, 1° and 0.01 KW, respectively. Within the chosen period, the data missing rate is 0.42% and the longest missing period is 63 hours. A missing period is filled with the observations for the same hour of the most recent day. In the time series of the Spanish wind farm, easterly wind, which is from the Iberian Peninsula, and westerly wind, which is from the coastline, is shown to prevail.

The Greek wind farms are from Crete, the largest island in the Aegean Sea. It has high wind energy potential and an autonomous electricity grid. From May to September, the Etesian, the strong dry north-westerly wind regime, prevails due to the monsoonal effect. The Bora, a cold northerly or north-westerly wind, blows in the autumn and often occurs in winter. During the winter season, the Sirocco, a southerly wind moving eastwards often accompanied by heavy rain, often arises and lasts as little as half a day or as much as several days. In the mountainous island of Crete, the channelling of the air flow by the coastal valley and sea breeze effects are combined and can increase or decrease wind speeds. The datasets from Aeolos, Enteka and Rokas, which are in the east of Crete, correspond to a period from 1 January, 2006 to 31 December, 2006, which amounts to 8,760 hourly observations. The data from Iweco wind farm, which is located in the centre of Crete, is over a shorter period from 1 January, 2006 to 30 October, 2006, which amounts to 7,271 observations. The original wind speed, direction and power production data were rounded to the nearest 0.1 m/s, 0.1° and 0.1 MW, respectively. The wind speed and direction were recorded at the hub height of one of the turbines in the wind farm. The wind power data corresponds to the total power generated from the whole wind farm. The capacities of the Aeolos, Enteka, Iweco and Rokas wind farms, at the end of 2006, were 11.6 MW, 2.8 MW, and 4.3 MW and 16.3 MW, respectively.

In our empirical study, the first 75% of the data is chosen for fitting the model parameters, and the last 25% of the data is chosen as the post-sample period. We rolled the forecast origin forward (one hour at a time) through the post-sample evaluation period to produce a collection of density forecasts for lead times from one to 72 hours ahead from each model for each horizon. We do not re-estimate model parameters for the different forecast origins. As a simple benchmark, we use persistence density forecasts, which are produced by kernel smoothing of the observations for the in-sample periods using three different moving window sizes, namely all in-sample observations, 12 hours and four hours. It is not to be expected that high quality density forecasts will result when kernel density estimation is applied to few observations.

B. Measures for Evaluating Density Forecasts

Necessary conditions for an ideal density forecast include calibration and sharpness. Calibration is a process correcting the statistical consistency between the predictive distributions and the realised observations, and that sharpness of a conditional density forecast is the concentration of the predictive distribution on the observation [16]. The ideal distribution for sharpness corresponds to the actual value y_t with zero variance. Regarding these criteria, the continuous ranked probability score (CRPS) by [17] and [18] are used in this paper. The CRPS can be applied to the evaluation of multi-step ahead density forecasts (see, for example, [19]). The CRPS is defined to be:

$$CRPS(F, y) = \int_{-\infty}^{\infty} (F(z) - I(z \geq y))^2 dz,$$

(6)

where y is a realised value, and F is the estimated cdf function. Since it is not straightforward to calculate the integral in the theoretical form of the CRPS, the empirical form of the theoretical CRPS [16] as in the following:

$$CRPS(F, y) = \frac{1}{n} \sum_{t=1}^n \left[E_F |Y - y| - \frac{1}{2} E_F |Y - Y'| \right], \quad (7)$$

where Y and Y' are independent copies of a random variable from the function F at time t , and E_F denotes the conditional expectation of the function F . Minimisation of the CRPS maximises the sharpness of the predictive distribution of the forecast model.

C. Evaluation Results of Density Forecasts

The density forecasts from various univariate models are evaluated and their CRPS and MAE values are presented for different forecast horizons in Tables 1 and 2. Each value of the tables is the average of the evaluation measures from a Spanish wind farm and four Greek wind farms. In Table 1, we report accuracy for the earlier lead times up to four hours ahead because it seems likely that, for short lead times, statistical methods have more to offer over atmospheric models. Table 2 summarises accuracy across all 72 lead times. In the tables, the bold font indicates the best performing method at each lead time. The lower the CRPS value is, the more the predictive distribution is concentrated on the realised value. Also, the lower the MAE value is, the more the expected value of the predictive distribution is close to the realised value. The threshold ARMA-GARCH models with up to three regimes in level and volatility in expressions (1-4) are compared. The lags of each model is selected by the Schwarz's Bayesian Criterion (SBC). These models are also compared with persistence benchmark models, which are kernel smoothing of in-sample data, kernel smoothing of the most recent 12 hours and kernel smoothing of the most recent four hours of data.

In terms of CRPS, overall, the AR(2)MA-GARCH(2) model, which has two regimes in both the AR component and the GARCH component, provided the most accurate density predictions for the forecast horizons up to four hours ahead. Further than four hours ahead, the AR(2)MA-GARCH(1) model, which has two regimes in the AR component and the GARCH component without regime-switching, produced the most accurate forecasts. In the forecast horizons up to 72 hours ahead, it is surprising that all the regime switching models performed better than the kernel smoothing persistent models and the basic AR(1)MA-GARCH(1), which does not contain regime-switching component in either level and volatility. In view of this, two regimes for the AR component were the most effective overall for the five wind farms in our empirical test.

Table 1: CRPS and MAE evaluation comparison. Each value is the sum of an evaluation criteria from 1 to 4 hours ahead, and then averaged across five data sets. Each row is sorted according to the CRPS evaluated for wind speed.

Model	Wind Speed CRPS	Wind Speed MAE	Wind Power CRPS	Wind Power MAE
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AR(2)MA-GARCH(2)	3599.1	4974.6	201.5	307.8
AR(3)MA-GARCH(2)	3600.2	4975.8	201.5	307.3
AR(2)MA-GARCH(1)	3601.2	4977.6	201.4	307.1
AR(1)MA-GARCH(1)	3606.1	4979.9	201.4	308.4
AR(1)MA-GARCH(3)	3609.7	4983.2	201.2	308.4
AR(3)MA-GARCH(3)	3612.7	4996.8	201.5	309.0
AR(1)MA-GARCH(2)	3619.1	4999.5	201.8	309.6
Kernel Smooth (4 hours)	3908.4	5108.0	183.3	263.5
Kernel Smooth (12 hours)	4740.5	6427.7	207.6	302.6
Kernel Smooth (in-sample)	8689.9	12919.8	364.9	590.1

Table 2: CRPS and MAE evaluation comparison. Each value is the sum of an evaluation criteria from 1 to 72 hours ahead, and then averaged across five data sets. Each row is sorted according to the CRPS evaluated for wind speed.

Model	Wind Speed CRPS	Wind Speed MAE	Wind Power CRPS	Wind Power MAE
AR(2)MA-GARCH(1)	8059.3	11597.7	383.6	608.7
AR(2)MA-GARCH(2)	8067.3	11615.9	384.7	611.2
AR(1)MA-GARCH(3)	8094.8	11571.7	386.2	611.7
AR(3)MA-GARCH(3)	8105.4	11663.4	387.7	615.0
AR(1)MA-GARCH(2)	8121.0	11623.5	387.2	614.1
AR(3)MA-GARCH(2)	8152.1	11716.1	389.3	616.2
AR(1)MA-GARCH(1)	8152.3	11635.1	388.6	615.0
Kernel Smooth (in-sample)	8676.8	12912.8	365.1	590.2
Kernel Smooth (12 hours)	9685.6	13909.8	358.0	500.6

Kernel Smooth (4 hours)	10974.0	13074.2	410.3	523.7
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Interestingly, the best performing model in wind speed, in terms of CRPS, was not always the best performing model in wind power when converted using the conditional kernel density. This might be due to (1) the stochastic relationship between wind speed and wind power; and (2) the exponential smoothing along the time dimension within the conditional kernel density.

Among persistence models, the smaller the kernel smoothing window size, the better it performed for the shorter horizon and the worse it performed for the longer horizon. All the models we propose outperformed the persistence models for lead times up to 72 hours ahead.

4. Summary & Conclusion

In this paper, we found that there is a benefit in accommodating regime switching in both level and volatility processes of wind speed time series, using the threshold ARMA-GARCH modelling. No study so far has explored the application of a regime switching model to the volatility process of a wind speed time series.

In future work, we plan to develop further the regime switching idea in the bivariate ARMA-GARCH by modelling both wind speed and direction together in the Cartesian coordinates and apply different distribution assumptions, such as Student t and skewed t distributions.

Acknowledgement

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Sensitivity of Offshore Wind Turbine Operation & Maintenance Costs to Operational Parameters

Iain Dinwoodie¹, David McMillan²

¹Centre for Doctoral Training in Wind Energy Systems, Department of Electronic and Electrical Engineering, University of Strathclyde, United Kingdom

² Institute for Energy and Environment, Department of Electronic and Electrical Engineering, University of Strathclyde, United Kingdom
iain.dinwoodie@eee.strath.ac.uk

Abstract

Due to the lack of operator knowledge and the deployment of new technology in future large offshore wind farms, significant uncertainty exists in the field of offshore wind farm operation and maintenance (O&M). In order to investigate this uncertainty as well as explore the feasibility of novel O&M strategies, simulation is required. This paper applies an autoregressive (AR) climate modeling approach to concurrently simulate representative wind and wave time series coupled with Markov Chain Monte Carlo (MCMC) based failure simulation. The AR climate modeling approach allows a synthetic time series to be rapidly produced based on site data. The hourly short term correlations as well as medium term access windows of up to several days required for maintenance operations are captured while preserving the overall observed distribution and seasonality.

Failures are simulated based on failure rates and associated time to repair is based on the simulated weather climate. This time series based approach allows constraints on access vehicle capabilities, type and availability to be applied and the influence on wind farm availability and O&M costs examined. Lost earnings associated with downtime are also captured using the simulated wind speed time series.

Case studies, examining the influence of failure classes on operational modeling as well as an investigation into how turbine size influences the breakdown of operational costs are presented. A further study, exploring the degree to which overall O&M costs are influenced by variation in vessel access constraints is also shown, demonstrating the capability of the modeling approach. Novel areas for investigation are identified for future work highlighting the capability of the approach.

Keywords – Offshore Wind, Reliability, Cost Model

Introduction

Onshore wind power is the most mature renewable technology and operators have obtained significant experience in operation and maintenance (O&M). The most common operating approach for large onshore wind farms is a combination of scheduled and reactive

maintenance, restoring components after failure. This approach has proven to be cost effective while availabilities of over 97% have been achieved [1]. During the last decade offshore wind has experienced substantial growth to a worldwide installed capacity of over 3GW focused in Northern European waters. In addition, offshore projects currently at the scoping or development stage in Europe exceed 100GW in capacity, representing a potentially huge market [2].

The large capital expenditure associated with offshore wind has resulted in a considerably different market structure from onshore wind. Offshore, there has been a lack of diverse operator experience and a conspicuous lack of failure databases such as those available for onshore [3-5]. Additionally, many larger offshore wind farms are still operated under warranty. The result is that significant uncertainty surrounding offshore failure characteristics exists and early offshore wind farms have tended to adopt conventional onshore operational strategies. The uncertainty and conventional O&M approaches have contributed to poor availabilities of around 80% as well as wide variation in annual performance between sites [6, 7]. Similar uncertainty exists around the costs of O&M with estimates ranging from 20 – 33% of overall project cost [8, 9]. Even at lower estimates this represents a huge financial investment with significant scope for savings. It is therefore necessary to identify which components have a critical influence on operations and to quantify the benefits of alternative operational strategies.

Methodology

To understand the key influences and gain greater insight into the potential benefit of using advanced asset management approaches a body of work in the field has developed. Reviews covering the broad range of work in the field are presented in [10, 11]. Various methodologies have been used to represent the O&M process of wind turbines. Analytical approaches such as [12] allow sensitivity analyses to be performed rapidly but are limited in their complexity and simulation approaches are more prevalent. The approach developed in [13] uses statistical representation of failures, weather climate and access delays and is well established in the industry; it allows prediction of costs for a site with known conditions. However, in order to examine the operational stage of wind farms it is necessary to use a simulation approach with a synthetic wave height time series determining access, various commercial and research models have adopted this general approach [10].

The meteo-ocean modeling approach adopted in this work has not previously been applied to offshore wind O&M. As well as helping to reduce uncertainty by providing alternative methodology to the industry, the approach in this paper has several beneficial features that are outlined in this paper. The resulting model allows for an accurate assessment of losses associated with down time as well as the ability to investigate advanced operating strategies.

Monte Carlo Markov Chain Failure Model

The approach to simulating failure behavior in this work is described in [14]. The turbine is represented as a series of subsystems with known failure rate, λ defined in equation 1. Each subsystem may exist in one of a finite number of states and at each

simulation time step will remain in that state or move to another state with a specified transfer probability. With sufficient knowledge of a system, deterioration can be represented using several system states as well as interdependencies between subsystems [15]. Currently, an adequate level of system knowledge is unavailable nevertheless the methodology presented in this study could be extended to incorporate this if detailed system knowledge becomes available.

The simplest representation of an engineering system was adopted where each subsystem is statistically independent and is represented as a binary system either operating or failed. The transition probability of moving from an operating state to a failed state is governed by the failure distribution of the subsystem. The failure characteristics of onshore wind turbines have received some examination [5, 16] however no comparable work exists for offshore turbines. For this study it has therefore been assumed that failures have an exponentially distributed probability distribution, corresponding to random failures under normal operation. With this assumption, the probability of a failure occurring during any time step is described in Eq. (2).

$$\lambda(t) = \frac{f(t)}{N(t)} \quad (1)$$

$$U(t) = 1 - e^{-\lambda t} \quad (2)$$

To implement this in the simulation, a random number is generated in the range zero to one for each subsystem and compared to the corresponding probability obtained in Eq. (2). Where the random number exceeds the specified value, a failure occurs. A single simulation run covers 20 years, a typical expected lifetime of a turbine. A sufficient number of simulations are performed for the results to converge and the overall availability then calculated.

A turbine is deemed operational if no subsystems are in a failed state. A solution of Eq. (2). for each subsystem at each time step is required and overall availability determined by looking at the ratio of time steps when all systems are operating to those where at least one system is down. With adequate knowledge of the system, advanced features such as redundancies or the ability to operate the overall system at reduced capacity under failure of individual subsystems could be investigated.

AR Climate Model

Auto-Regressive modeling approaches to describe time series data were first developed in [17], and have since been applied to a diverse range of applications. Of particular relevance to this work, AR models have been used to successfully describe significant wave height time histories [18], wind speeds for wind turbine power generation [19] and wind speed based wind turbine maintenance [20]. The AR models, normalized by the mean of the data are described by Eq. (3).

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^p \varphi_i (X_{t-i} - \mu) \quad (3)$$

This equation is valid only for a process having a Normal (or Gaussian) distribution. Neither annual wind speed nor significant wave heights follow a normal distribution and must therefore be transformed before Eq. (3) is applied to the data sets.

It has been demonstrated that for mean wind speed removing a fit of monthly mean and diurnal variation from observed data results in the annual distribution approximating a Normal distribution. For significant wave heights it is necessary to remove a fit of monthly mean values and then apply a Box-Cox transformation on the data shown in Eq. (4) [18].

$$Y_t = T(Hs_t) = \ln(Hs_t) - \hat{\mu}_{\ln(Hs_t)} \quad (4)$$

The required order of AR model in each case was determined using the auto-correlation function and partial autocorrelation function and determined as 2 and 4 for wind and wave models respectively. The determination of AR coefficients and model generation was performed using the MATLAB system identification toolbox. Figure 4 shows a sample original and transformed data set as well as a sample simulated time series of significant wave height. From Figure 4 it is evident that the simulated time series displays common characteristics with the original data. The simulation is deemed acceptable if it captures the short, medium and long term characteristics of the observed site. Figure 4 also shows the ability of the modeling approach to meet these criteria additionally, seasonality is captured

By using a common modeling approach for both wind and wave climate it is possible to introduce correlation between wind speed and wave height. This is introduced by using a common random noise component with an appropriate time lag. The AR modeling approach is computationally simple and a large number of synthetic time series' can rapidly be produced.

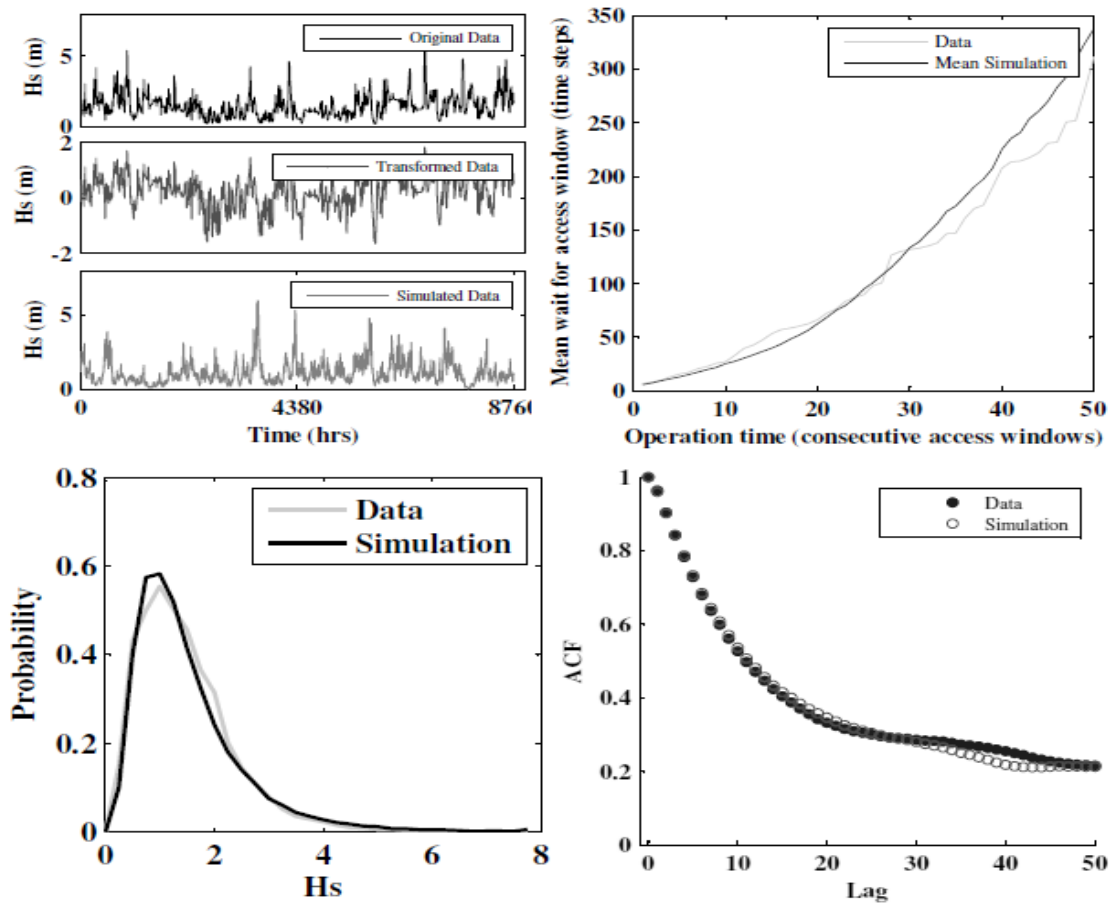


Figure 4. Input data and simulation outputs showing ability of model to capture key weather parameters

Cost Model

The cost model comprises of several components, lost earnings, repair cost, vessel cost and staff cost all normalized to the amount of energy produced in kWh. The value of energy produced is determined using manufacturer specified power curve, the simulated synthetic time series and the turbine state, as shown in Eq. (5). For this study, the losses associated with arrays are included as an array efficiency term in Eq. (5).

$$P = P_{pc} \times U_{sim} \times S_{turbine} \times \eta_{array} \quad (5)$$

$$LE = P \times (MV_{elec} + MV_{ROC} * ROC_{Band}) \quad (6)$$

Lost revenue is calculated from Eq. (6) when a turbine is in a failed state, with the output of Eq. (5) multiplied by an average wholesale electricity cost. For the analysis in this paper an additional component, representing the value of the Renewable Obligation Credit (ROCs) in the UK market is included in the lost revenue analysis as well as the current banding for offshore wind. Sensitivity to the value of the wholesale electricity, the value of ROCs and the banding of ROCs can therefore be examined by varying these parameters.

Minor repair costs representing faults that can be remotely fixed or tolerated until the next scheduled service or turbine visit for major repair are allocated a fixed value across all subsystems. These represent less than 5% of total repair costs despite representing approximately 75% of total failures. The methodology and consequence of including failure classes in this work is discussed in the results section. The cost of replacing major components is based on the [21] which produces cost of components based on machine rating and diameter size along with current commodity prices. Using this model, estimates of the component cost of hypothetical future large turbines were produced and these values used as the repair cost for major failures.

Vessel costs have two components. The minimum fixed cost is determined by the duration of a repair operation as well as day hire rate of a suitable vessel. Several classes of vessel, crew, small lift, large lift and jack-up boats are required dependent on the mass of components requiring repair, calculated from [21]. In addition, a cost is associated with the waiting time between a failure occurring and an adequate access window to perform a repair operation being identified. Scenario one would represent an operator hiring a suitable vessel as soon as a fault is identified for the entire duration of the waiting time and scenario two would represent an operator only hiring a vessel for the duration of the operation. In an operational wind farm, various factors would influence the actual cost to the operator. In particular, forecasting accuracy, lead time on vessels and individual contracts with vessel operators would determine actual waiting time costs at a specific site. In this model the value of the first, worst case scenario is calculated and is multiplied by a waiting time coefficient between 0 and 1 to represent real world which would be between the two extremes.

The final cost component of O&M model is staff cost. Staff costs comprise of a fixed number of permanent staff on a per-turbine ratio as well as additional staff for the duration of repair operations. The number of additional staff required can be varied to represent the size of the component requiring repair in a similar manner to the vessel category but this has little impact in the overall cost and a fixed number of extra staff for each major repair operation has been applied for this study

Analysis

Data and Methodology

Unlike the onshore wind industry where a large and varied quantity of operational data and experience has built up, relatively little knowledge exists offshore and this significantly adds to operational uncertainty. Onshore reliability databases comprise of a variety of site conditions as well as significant variation in turbine sizes and configuration and are unlikely to be representative of offshore turbine performance. Currently, a similar offshore reliability data has failed to emerge and due to the small number of offshore wind farms operating out with OEM warranty period it is unlikely that such a database will be established for a considerable time. There has been a limited volume of data released into the public domain, principally from projects that have received government funding [6, 7] which forms the basis of the failure rates and repair times in this study. Although this is a small sample size, the greater uniformity in site conditions as well as turbine size and configuration in the offshore market allows the data to be considered representative of the industry at current.

A. Influence of Failure Categories

It has been proposed that the use of a single failure rate for subsystems, which has been considered adequate onshore, is no longer sufficient when considering the offshore case [22]. A case study, using the observed failure rates and site conditions at the from [6] has been performed to evaluate the impact of not considering failure classes on failure modeling. The results of this analysis are shown in Figure 5.

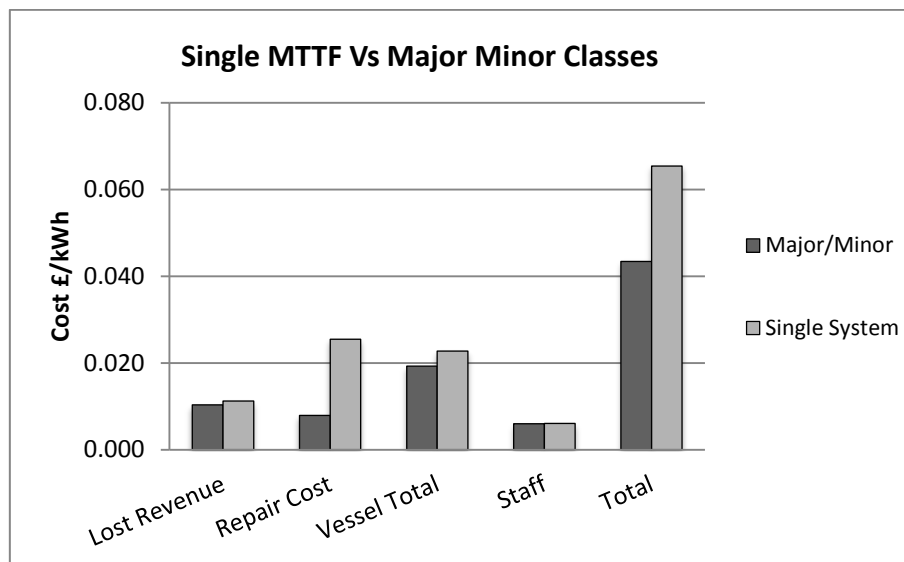


Figure 5. O&M cost breakdown with single and multiple failure classes

From Figure 5, it can be seen that only considering a single failure class results in a significant overestimation of O&M costs. This difference is principally due to the higher repair

costs as each failure requires a significant repair operation as well as slightly increased vessel costs associated with larger repair operations. This result is consistent with the analysis of [22] and highlights the importance of considering different failure types for each subsystem to correctly identify key cost drivers. Considering only a single MTTF predicts O&M costs to be 50% higher than considering minor faults separately from major failures. Typical repair costs for offshore wind farms have been reported as 0.02 - 0.04 €/kWh, slightly below the estimate of this study. The data used in this case study included a major drivetrain overhaul which accounts for the estimates being at the upper end of the observed industry costs. In addition, lost revenue is not always considered a direct O&M cost but has been here for a complete cost analysis. For the investigation of turbine size and access constraints, onshore failure rates for these subsystems were used, bringing overall costs in line with those seen in operational farms.

B. Access Threshold Analysis

A key issue associated with offshore wind energy is the limited access due to wave climate. Despite being close to shore, accessibility at UK R1 sites has been observed to vary widely from 50% to 90% with an average of 69% [7]. As developments move further offshore into more volatile wave climates, there will be greater risk of sites being inaccessible. It is recognized that there is a relationship between accessibility and availability and improving the access constraint of vessels will improve wind farm availability. However, little attention has been paid to the cost implications associated with improving access thresholds. A case study, exploring the operational cost benefit of improved access threshold has been completed.

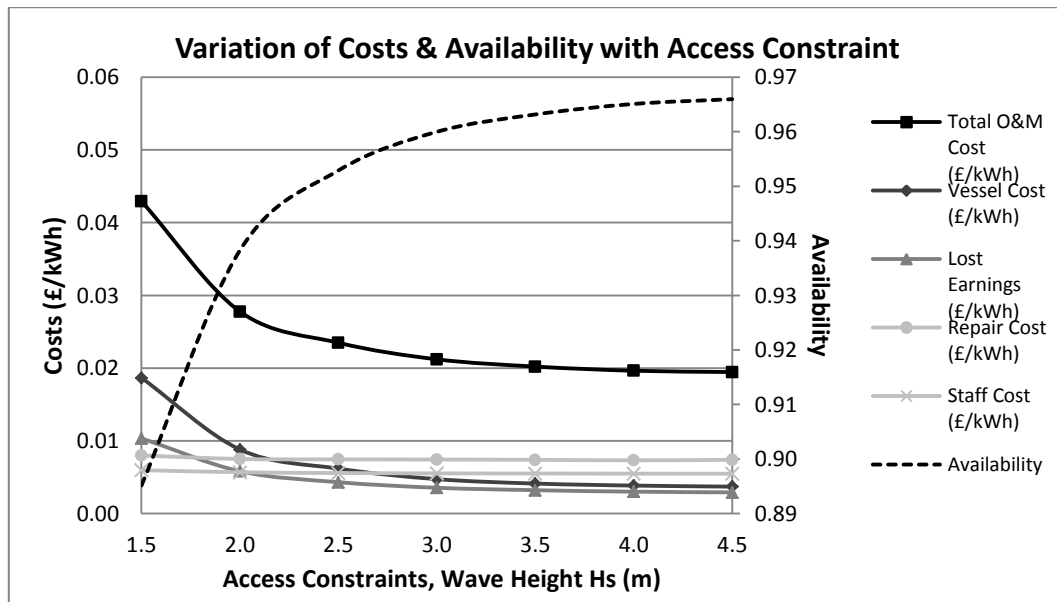


Figure 6. Influence of vessel access threshold on operational costs

Figure 6 shows availability and operational costs against access vehicle capability. It is observed that both vessel cost and lost earnings fall sharply with a 1m increase in access constraint while repair and staff costs see little to no change. In this study there has been no associated cost increase with improving the vessel operability but in reality this would be likely to happen. From Figure 6 it can be determined that an operator would still see an overall reduction in O&M cost from paying double the daily hire rate for vessels that could increase the access at a site from 1.5 to 2m Hs. In this study, all classes of vessel are constrained by the same wave height although this could be modified to further analyze cost benefit decisions for individual vessel types on overall costs.

C. Influence of Turbine Size

As technology has matured the feasible size of wind turbines has increased to the multi megawatt range with 5MW offshore technology in commercial operation and 10MW machines in the early stages of development. Much of the drive towards larger machines has been the idea of economies of scale reducing costs. It has been proposed that for a given wind farm capacity there will be a cost reduction from having fewer, larger machines. This is due to fewer installation operations costs and fewer turbines to maintain. Offsetting these benefits is the increased cost of each operation as well as greater loss of earnings associated with downtime for a large machine. A case study exploring the consequences of using larger wind turbines on overall operational costs has been performed.

It has been identified in [21], that the costs of different wind turbine subsystems do not increase proportionally to each other as the size of turbines increase and a set of empirical laws for each subsystem size and cost has been developed. Using blade sizes from commercially available 3MW, 5MW and 7MW offshore turbines and estimating a 10MW blade size the cost of various components for 4 machine sizes were calculated and are shown in Figure 7.

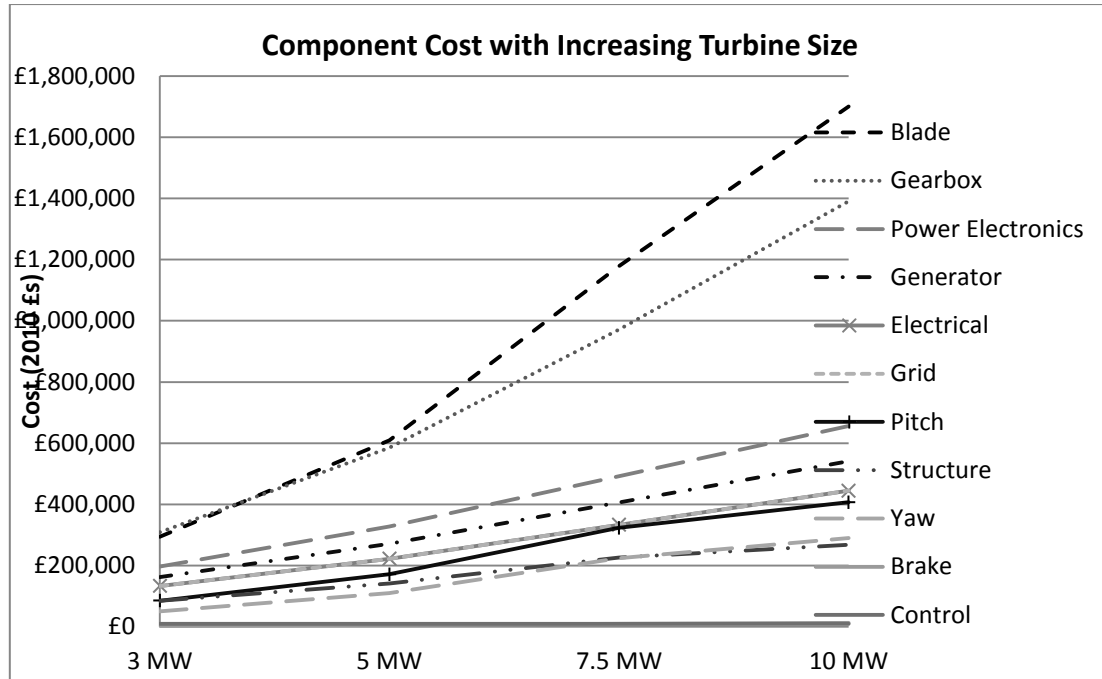


Figure 7. Component cost variation with turbine size

From Figure 7 it is evident that the blade and gearbox costs become increasingly significant at larger turbine sizes while the cost of some systems such as control are independent of size. The increased cost of components is compensated by the larger energy capture of larger. In order to determine the net result, the power produced by each turbine size must be considered. Turbines with the same nameplate rating may have significantly different power curves and power curves for very large turbines may be theoretical or not exist at all. For this investigation the 5MW turbine power was selected as the reference and scaled to each of the other sizes. Currently, there is uncertainty over the relationship between failure rates and turbine size in the offshore case, therefore failure rates were taken to be constant for each turbine size. Simulations representing the expected 20 year life cycle of a modern turbine were performed and recorded. The mean results and standard deviation are shown as absolute costs in Figure 8 and as percentage of overall cost in Figure 9.

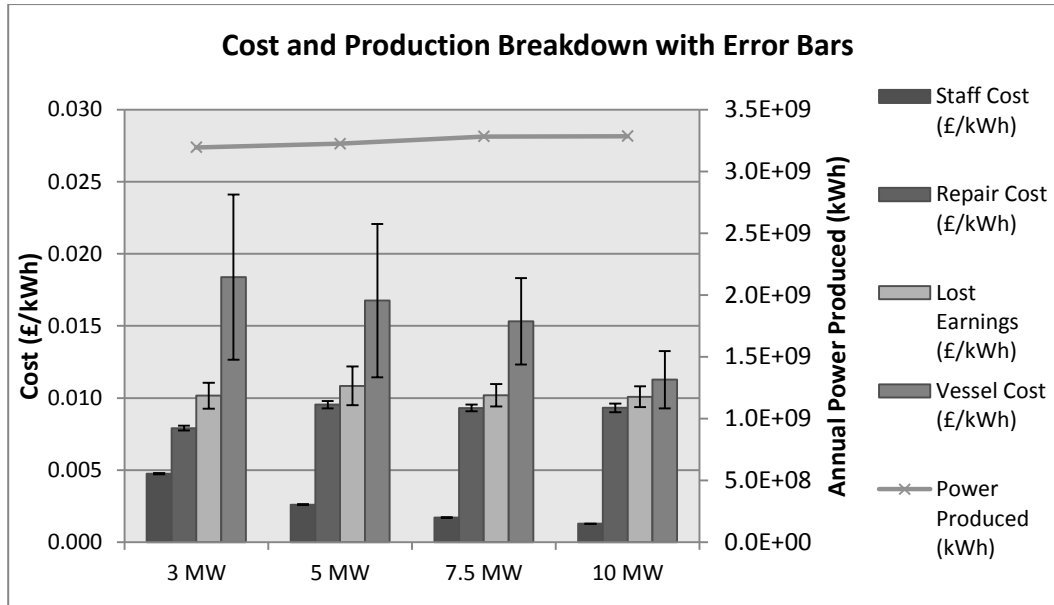


Figure 8. Effect turbine scaling on operational costs

From Figure 8 it is observed that while there is little change in annual power produced, there are significant changes in operational costs. The largest change is observed in the vessel costs where increased turbine size reduces cost. This is explained by the decreased number of transfer operations associated with the smaller number of turbines, despite a slight increase in the cost of individual operations due to larger vessels being required. Similar gains are observed in staff costs as with fewer turbines to manage, fewer staff are required. However, there is no significant gain in repair cost as the increased cost of repairs cancels out the advantage of having fewer repairs to perform. Lost earnings are related to overall availability and are largely unaffected by turbine size.

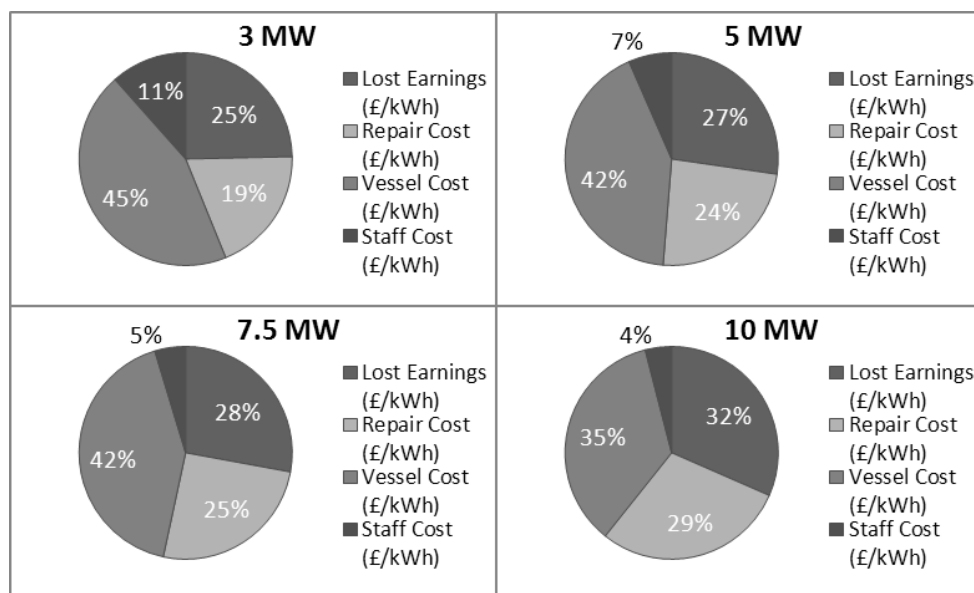


Figure 9. O&M cost percentages with changing turbine size

Figure 9 identifies that as turbine sizes increase, repair costs and lost earnings become more significant contributors to overall costs. When considering future large wind farms where higher capacity wind turbines are used, there will be a more significant benefit from reducing failure rates and costs associated with component repair and replacement. In all cases vessel costs contribute the largest percentage of costs as well as the greatest degree of uncertainty, identifying this as the key component of overall costs to control.

Conclusion

The ability of an AR wind and wave modeling approach coupled with stochastic failure modeling to examine cost drivers for offshore wind farm operation and maintenance has been demonstrated. Due to the large number of variables and uncertainty surrounding offshore O&M, the industry will benefit from using as wide a range of analytical approaches as possible. The AR methodology allows synthetic, correlated time series of both wind speed and wave height to be rapidly generated that maintain the short, medium and long term characteristics of observed data. Additionally, the common modeling approach adopted for wind speed and significant wave height allows observed correlation to be captured. This is of particular importance for future larger wind turbines where costs associated with lost earnings contribute a larger percentage of overall operational costs.

Several case studies have been performed in order to demonstrate the capability of the modeling approach. Key modeling considerations for offshore wind have been identified. The necessity of including different failure modes in the offshore environment and the need to fully develop the relationship between operational costs and availability has been established. The modeling methodology has been developed in order to identify and quantify the sensitivity of overall costs to key operational parameters and to allow analysis of novel asset management techniques and turbine configurations to be investigated. The synthetic time series approach allows constraints relating to resources and decision making to be implemented for the investigation of overall operational strategies. By coupling this with a scalable cost model, alternative methodologies for operating future large scale offshore wind farms can be assessed.

Acknowledgements

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Nomenclature

$f(t)$	Observed Failure Rates	$\hat{\mu}_{1n(Hs_t)}$	Fourier Series fit of log means
$N(t)$	Observed Time Period	ϕt	AR parameter
H_s	Significant wave height	P	Power Out
p	AR degree	P_{pc}	Power Curve Power
$U(t)$	Failure likelihood function	U_{sim}	Simulated Wind Speed
X_t	Modeled time data	$S_{turbine}$	Turbine Operational State
Y_t	Transformed time series	LE	Lost Earnings
ε_t	White noise disturbance	MV_{elec}	Wholesale Electricity Price
$\lambda(t)$	Failure Rate	MV_{ROC}	Renewable Obligation Credit Price
μ	mean of data	ROC	ROC Banding

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RAMS-database for Wind Turbines

Lars Pettersson¹, Cecilia Orbert²

¹<Vattenfall Research & development>, <Sweden>

²< Vattenfall Research & development>, <Sweden>

lasse.pettersson@vattenfall.com

Abstract

During 2010 Vattenfall made a pre-study, supported by Vindforsk in Sweden and Norway. The subject was design of a RAMS-database for Wind Turbines. This included an outlook to see what is being done in this area and where good examples may be found. What can be learnt from inside and outside the wind industry?

Assuming a reliability database will be designed and implemented – what are the possible options between which we can make a choice? If option A is selected then what are the consequences of that, option B etc? A set of recommendations was also made with 2 possible levels of ambition.

One important conclusion from this study is that such a database, if created, should be designed to support maintenance and more precisely Reliability-Centred Maintenance RCM (or similar). Other possible users of such data can use this maintenance-related data.

This was almost 2 years ago. Within Vattenfall no decisions have been taken regarding RAMS data collection since then.

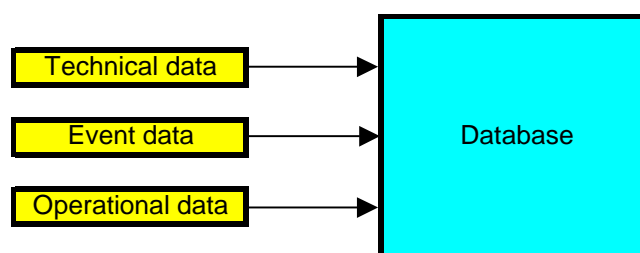
Keywords – (RAMS-database, reliability database, Wind Turbines)

Introduction

A quickly growing sector of electricity production is wind power. Increased knowledge related to many aspects of wind power is highly in demand and reliability aspects is one area where a lot of activity is performed worldwide. This paper discusses one important aspect for improving reliability of wind turbines – reliability data.

The report contains an outlook to see what is being done in this area and where good examples may be found. What can we learn from inside and outside the wind industry?

Assuming a reliability database will be designed and implemented – what are the possible options between which we can make a choice? If option A is selected then what are the consequences of that, option B etc? A set of recommendations is also made with 2 possible levels of ambition.



The figure above gives a broad introduction to what kinds of data are included in a Component reliability database.

One conclusion from this report is that such a database, if created, should be designed to support maintenance and more precisely Reliability-Centred Maintenance RCM (or similar). Other possible users of such data can use this maintenance-related data.

This paper is a short version of the Report < Ref 1>.

Purpose and goal

Purpose

The existence and use of a RAMS-database may significantly increase the knowledge of components and their behaviour in different environments. That will benefit operation and maintenance as well as swedish/nordic competence within the Wind Power area.

Increased knowledge on properties of components enables improved maintenance which is a basic precondition for high availability and low operating costs.

A RAMS-database will also create data for research use in universities and institutes. Models can be developed based on real data instead of hypothetical data.

A main purpose of the pre-study is to illustrate how the benefit of a RAMS-database will be affected by alternative possible designs (not IT-aspects) and organisation of the database.

Goal

The goal of the project is to present material for further discussion and work on how to set up a RAMS-database for wind turbines.

Topics of the project:

1. A description of some existing RAMS-databases. Content, organisation and use.
2. A description of state-of-the-art concerning use of reliability within Wind power today. (Not discussed in the paper.)
3. A discussion on possible organisations of database and data collection.
4. A survey of the interest from some major possible stakeholders in a RAMS-database. (Not discussed in the paper.)

Delimitations

This is not an IT report. It does not consider software solutions or other specific IT-related aspects.

Another limitation is that it does not discuss "Information needed to operate and maintain Wind Turbines". It is aiming at aspects closely related to component reliability.

The original Report <Ref 1> includes a section on State-of-the-art within wind industry but this is now excluded since the pre-study was made 2 years ago and it may be out-of-date.

General

RAMS is short for "Reliability, Availability, Maintainability and Serviceability/Safety)" (both Safety and Serviceability are used when explaining RAMS).

A RAMS-database may be of major importance for maintenance, operation, investment, production and development of units. It is not the main focus of this paper to motivate a

RAMS-database but rather discuss the possible alternatives of design and organisation. However a preliminary statement on the main uses of such a database is needed and it is the opinion of the authors that the main profit is related to maintenance aspects.

It is essential in the maintenance environment to have efficient access to knowledge about components and their properties in the current environment. A RAMS-database is one such source of knowledge.

In this report from now on the term component reliability database (CR-database) will be used. Such a database can supply information for RAMS purposes.

Some existing databases in other industries - general

Introduction

One reference for a discussion on wind-power reliability databases is a description of a few existing component reliability databases outside the wind-domain. The point of this is to give a kind of state-of-the-art.

Systematic reliability work is more used in some sectors than in others. Space/air, nuclear and offshore oil/gas-industries are sectors where reliability plays an important role and for this reason it seemed natural to identify reliability databases from those areas. We also preferred databases related to the Nordic countries since conditions world-wide may be different elsewhere and the reliability database which is the goal for this paper should have a strong relation to the Nordic countries.

The two databases described here are TUD nuclear and OREDA for offshore oil/gas industries. These two were obvious choices since they are internationally known reliability databases with a strong relation to the Nordic countries. <Ref 1> describes some more Databases.

At first there is a chapter on different types of databases and the relations between them.

Different types of databases and the relation/difference between them.

General

The title of this paper is “RAMS-database for....”. So what do we mean by RAMS-database. There are a number of databases where reliability/RAMS data is stored. But this paper has a more precise topic – to provide information on the reliability of components in Wind Turbines. Below is given a description (rather than a definition) of an availability database, a CR-database (explained below), a maintenance system and an RCM-database.

Availability database

An availability database normally is common for a company or a group of companies. It may be national or international.

This is not a common term but used here for clarification. One common measure for a power plant (for example) is availability. A definition is “The available capacity of a thermal unit or station at any given moment is the maximum power at which the station can be operated for a given period under the prevailing conditions assuming unlimited transmission facilities.” <Ref 2>

An availability database contains information on availability and unavailability. It may also contain information on reasons for unavailability. For example if a wind turbine is unavailable due to a turbine failure this should be recorded in such a database. Often it is also possible to calculate unavailability due to turbine errors, due to gearbox errors etc.

Normally also an availability database contains information on more than one unit. That is one point of such a database, to show availability of several units and sometimes also main reasons for unavailability of several units.

To distinguish between this and a component reliability database, as this term is used here, the availability database does not (normally) have any information besides the gearbox for example. What type of gearbox, what kind of failure occurred, how long time did it take to repair and to wait for maintenance crew etc. This type of information exists in a component reliability database and also in a maintenance system.

Component Reliability (CR) database

A CR-database may be far from the sites, not related directly to the maintenance organisation.

In a CR-database there is information that a gearbox failed, but also, why did it fail, how long waiting time for personnel, for spare parts, actual time to repair etc. In a reliability database there is also information on the components. What type of gearbox was this, how old is it, ratio, size etc.

The output of a CR-database is for example failure rates for gearbox type A and type B, repair time for type A and type B, reasons for gearbox failure, normally according to predefined groups, etc.

The TUD and OREDA databases described below are CR-databases.

The component approach looks at a site “from below” or from the component level – how do the components perform. This is different from an availability database that has the entire unit performance as a measure.

What is the difference between a CMMS and a CR-database? A CMMS may contain elements very similar to a CR-database but to be a “real CR-database” it should fulfil a number of demands where some of the more important are:

- A number of tools intended to estimate behaviour (most important are failure rate and repair time) of user defined groups of components. The user should be able to define a group of components and see reliability performance for this group.
- Contain equipment data, failure data and operating conditions.
- Contain information of a number of units (not just one).

Maintenance System (CMMS)

A maintenance system normally is accessible locally, at the unit or at a place where the maintenance organisation is based.

Maintenance Systems are designed to support a systematic work on maintenance and repair of industrial equipment and supplies. Such a system has a main user which is the maintenance organisation; planners, repair crew, purchasers, etc. This use normally is very concrete and “down-to-earth”. Examples of information such as

- repair this pump
- we have repaired the pump
- spare parts used were 2 bearings
- 2 men worked for 4 hours
- etc

A modern maintenance system normally consists of the modules for preventive, planned and corrective maintenance as well as for supplies and purchases. Storage, and purchasing of

parts are essential for the system because all purchasing is based on the objective to have safe access to suitable spare parts at the right time.

A CMMS is a software tool designed to support the maintenance department in all types of maintenance work.

RCM work and RCM database

Reliability-Centred Maintenance is a process used to determine what must be done to ensure that any physical asset continues to perform a required function in its present operating context <Ref 3>.

The RCM process (often) entails asking seven questions about the asset or system under review, as follows:

1. What are the functions and associated performance requirements of the asset in its present operating context?
2. In what ways does it fail to fulfil its functions?
3. What causes each functional failure?
4. What happens when each failure occurs?
5. In what way does each failure matter?
6. What can be done to predict or prevent each failure?
7. What should be done if a suitable proactive task cannot be found?

Functional breakdown in RCM is a normal procedure to define the objectives of maintenance in terms of user requirements. When performing RCM we must gain a crystal clear understanding of the functions of each asset together with the associated performance requirements.

The main reasons why the assets exist at all are described as primary functions. Most assets are expected to fulfil one or more functions in addition to their primary functions. These are described as secondary functions (protection, control functions etc).

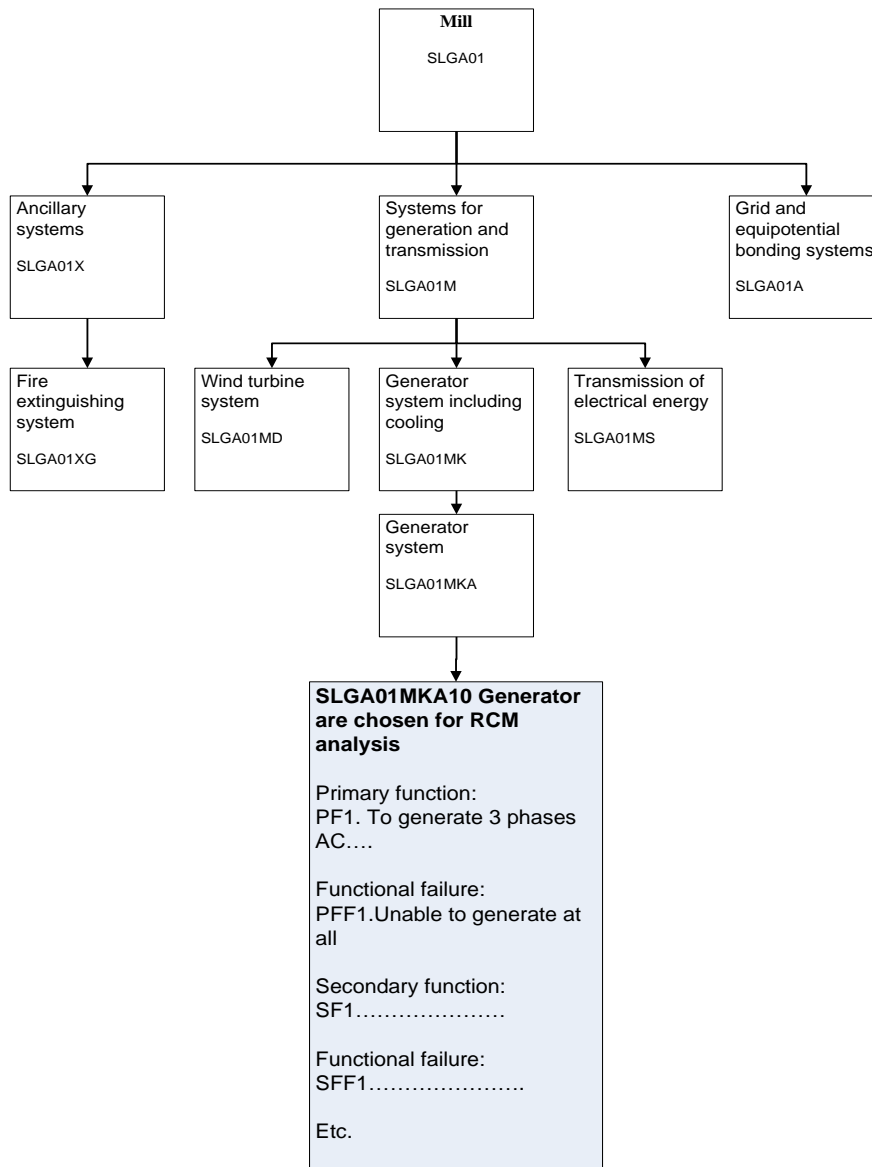


Figure 1: A Generator in RCM review

When performing a RCM-study we must decide where in the asset hierarchy we are going to describe the functions. Figure 1 shows a generator that is chosen for RCM review.

Functional failure is defined as the inability of any asset to fulfil a function to a level of performance which is acceptable to the user.

The event that causes a functional failure is called 'failure mode'.

RCM aims to identify all the failure modes which are reasonably likely to affect the asset under review, in this case the generator. The failure modes we are looking for is in or under the generator hierarchy (RDS).

The failure modes must also be defined in sufficient detail because maintenance is really managed at the failure mode level. For instance:

- Work orders or job requests in CMMS are raised to cover specific failures modes.
- Day-to day maintenance planning is all about making plans to deal with specific failure modes.

- In most industrial undertakings, maintenance and operations people hold meetings every day. The meetings usually consist almost entirely of discussions about what has failed, what caused it, what is being done to repair it and – sometimes - what can be done to stop it from happening again. In short, the entire meeting is spent discussing failure modes.
- To a large extent, technical history recording system (CMMS) record individual failures modes or at least, what was done to rectify them.

It is in the failure mode level that RCM-work needs the reliability data from CR-database or maintenance information from CMMS.

When performing RCM we need to document failure modes, the evidence of failure, in what ways it poses a threat to safety or the environment, in what ways it affects production or operations, if secondary damage is caused by the failure and what must be done to repair the failure.

The failure mode itself can be identified from work orders if the work orders containing type of failure and reasons for failure.

It is common practice to create a RCM database during the RCM-work.

The outputs from an RCM-database are

- Predictive and Preventive Maintenance tasks
- Modification requirements
- Components with strategies “run to failure”

If a CR-database does not exist we must rely on what the CMMS database can give us. At best it can give us the following information:

- Technical data (What type of gearbox was this, how old is it, ratio, size etc.)
- Spare part index
- Current Operational Context
- Current maintenance plan
- Occurred failures taken from the work orders containing the following information:
- Failure description and RDS key
- Failure cause
- Failure detection
- Corrective maintenance actions
- Time for repair
- Waiting time for spare parts, tools, personnel
- Downtime (total amount of time the asset would be out of service)
- Maintenance cost

If we do not have a CR database, the following information is missing or is insufficient

- Failure rates or MTBF for different components

An RCM database is normally common for only one company. It may or may not be connected to a CMMS or a CR database.

Nordic nuclear database TUD

Introduction

TUD system is an "information system for collecting, processing and presentation of failure statistics and reliability data".

The system's primary goal is to provide the power industry with operational data from nuclear plants for safety analysis such as PSA (Probabilistic Safety Assessment). The system is also designed to provide fault statistics in various forms.

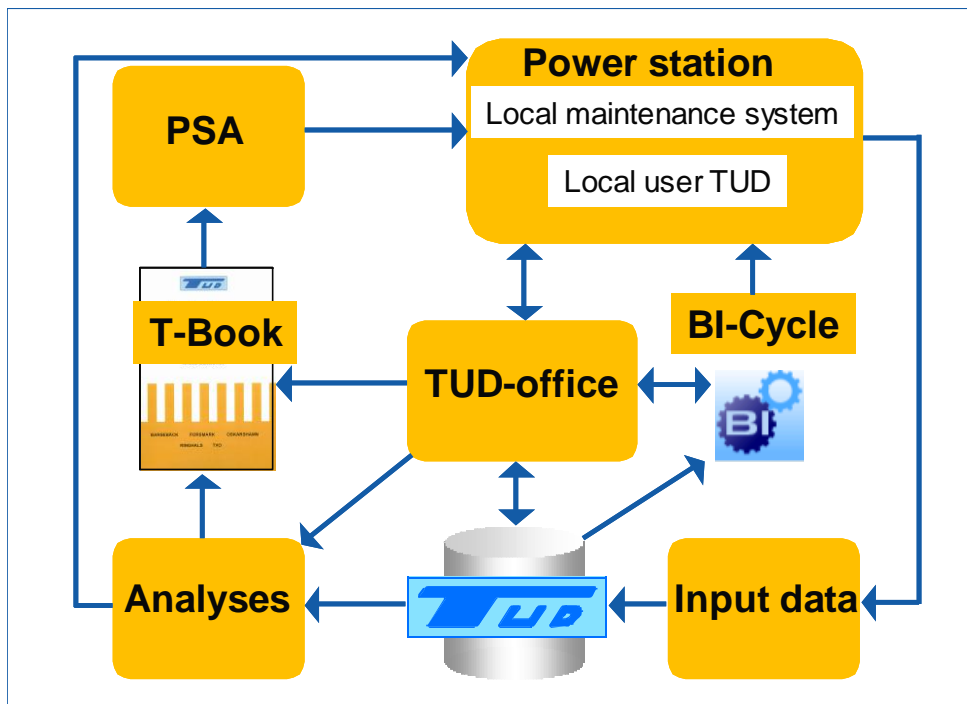


Figure 2: Overview of the TUD-system

Input

All information to TUD is retrieved from the local CMMS at the participating power stations. Each station itself decides how the desired information is collected and transferred to the TUD system. This implies that the collection has been integrated into the existing maintenance procedures to minimize the efforts and maintaining good input quality.

The TUD-system includes all systems related to process and safety. Minimum reporting are systems that are safety related. Apart from this, the power stations determine themselves which systems/components to be included in TUD-reporting.

Failure reports

For each failure event a failure report is written (into the CMMS) where the failing equipment is identified by the functional item for example "311V1". A number of codes and points of time are recorded as well as whether the functional item was able to function during the

failure time and repair. For the part of the functional item where some action was taken the functional type is written. For example the functional item Valve may consist of two functional types, the Valve itself and the Activator. One important ambition is also to get good descriptions in plain language in the failure report.

The transfer of failure reports from the nuclear power units to TUD takes place in a common format, monthly/quarterly or other specified periods.

The following terms are included in the transfer for the failure reports:

• Report type and no, Station code and Unit code
• System and component code
• Failure data codes <ul style="list-style-type: none"> - Detection - Failure effect - Failure type - Action - (Effect of failure on system/unit) - (Reason for failure)
• Points of time <ul style="list-style-type: none"> - Time of failure detection - Start of unavailability - Start of repair - Available after repair
• Repair effort <ul style="list-style-type: none"> - Man-hours - Average number of men
• Component category
• Description in plain language for <ul style="list-style-type: none"> - Failure observation - Failure type and cause - Action taken

Table 1: Content in failure reports

Component data

The largest amount of information is a CR-database inventory list. This contains background data for all relevant components.

This information is essential for a reliability data system, since all studied components must have a unique identification and all important parameters influencing reliability must be recorded. The identifying data is used to get a correct relation to the failure reports. It consists of the functional item id and functional type.

The information in the database is transferred to TUD from the local maintenance systems (CMMS).

Technical data are collected from the local equipment register in the CMMS and are intended to represent a true sub-set of these. Transmission of data takes place in a specified

format. It also includes, where necessary, conversion of the data from local register to the specified TUD format.

For each object type (pump, valve, etc.) a list is specified of what data to be transferred for each object type. Only the information contained in the local register (CMMS) is transferred to TUD.

Operating history (Operation Profile)

The quantitative basic facts (operation times to failure, number of demands, etc.) that are needed for the calculation of reliability values are supplied to the TUD-system in terms of the operating history (Operation Profile).

The purpose of this is to determine, for instance, the time a component has been in operation between two failures. The operating history is given by the time instances when the different operational conditions are changed. The identified operational conditions are:

- Cold shutdown
- Hot stand-by
- Start/stop-sequence
- Power production

Together with these conditions, information on turbine trips and reactor scrams are also collected.

Operating Time Readings and Number of Demands

For some components in a plant a better estimation of the operating time is obtained from the readings of operating time meters. These meters are read and transferred to the TUD system. By doing this, exact operating times of some components can be used in reliability computations.

For some components the number of starts is also retrieved. These values are stored in TUD as the sum of number of starts per year.

Certain functional items have an operating time meter connected. This applies in TUD's case, to primarily certain pumps, compressors/blowers and diesels.

Information on number of starts for selected functional items is needed for components in T-book.

Contents in the database (2010)

Section	Number
Failure reports	336000 reports
Component data	640000 components
Operation profile	14200 changes of operation profile
Operating time readings	2410 comp. with 61560 readings
No of starts	2470 comp. with 1420470 starts

Output

Output from the TUD is available through applications such as BI-Cycle and TUD 4.0 and also from the T-book.

T-book

For all nuclear stations a thorough safety assessment (PSA) must be made with fixed time intervals. The PSA is based on probabilistic assumptions of the unit models produced with event- and fault-tree-models.

The primary source for component reliability data in these analyses is TUD. For this purpose a special book – T-book – has been produced in order to have easily usable data of high quality in a simple form < Ref 4 >.

The T-book covers a subset of the components (about 23 000) which are covered in TUD. Special procedures for quality review of failure reports and checking against Licence Event Reports enables data of high quality to be obtained. T-book is updated regularly.

A special calculation program (T-Code) has been developed for the calculations carried out for T-book tables < Ref 5 >.

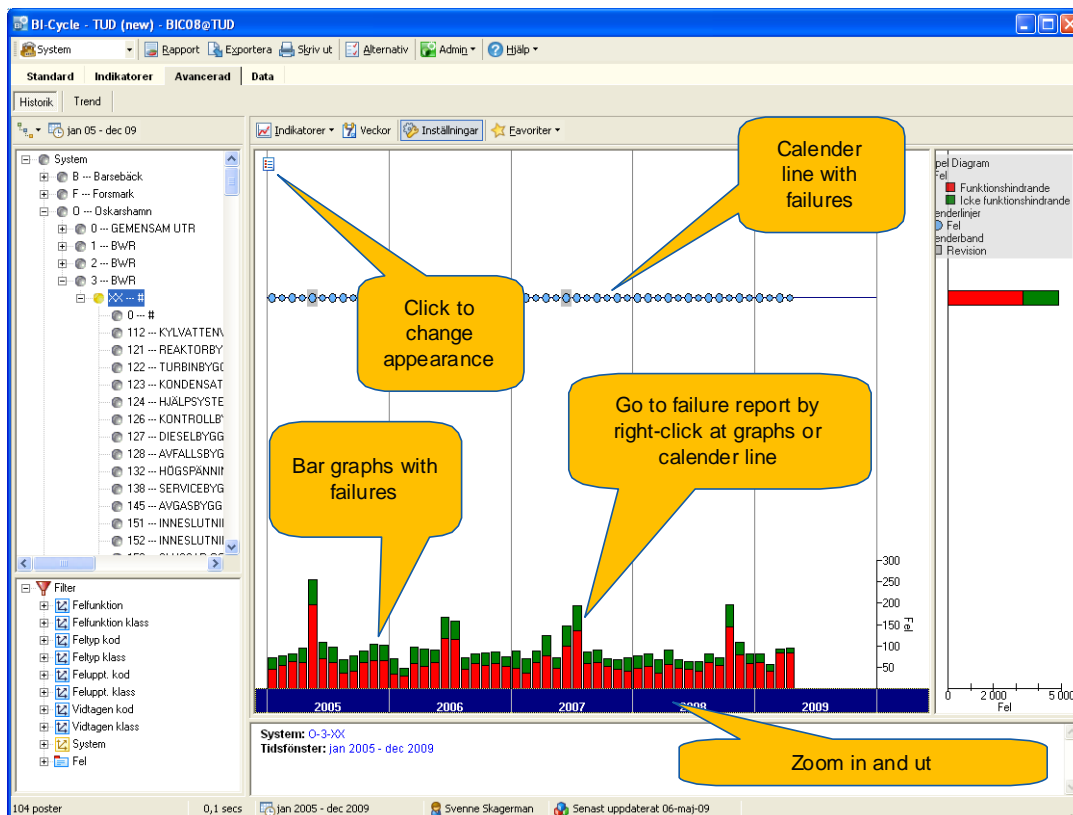


Figure 3: Bi-Cycle – module Advanced

BI-Cycle

The analyses tool BI-Cycle is available on all stations participating in the TUD-cooperation. Updated TUD-data is regularly transferred by CD-ROM to the power stations. Forsmark, Oskarshamn and Ringhals are using BI-Cycle both for analysing the TUD database and the local maintenance system database.

BI-Cycle stores information from many different sources. Engineering data, maintenance reports, failure reports and plant production data are consolidated in one data warehouse. The user can easily navigate through this data. History with big amounts of failure reports can be accessed in seconds.

Furthermore BI-Cycle gives the possibility to change the hierarchy and also filter, search and sort failure reports and engineering data.

A data tree allows you to navigate through the databases and the structure and a datasheet gives a structured picture over data from TUD that are stored in BI-Cycle.

TUD 4.0

Besides BI-Cycle there is also a PC-application (TUD 4.0) which is today mainly used by the TUD-office to manage the TUD-database. The TUD-application contains, apart from managing registers, screens for selection of failure events/components and screens to generate printable reports of failure events and calculation of reliability data. TUD-data is stored in a central server managed by the TUD-Office.

Access to information in TUD

The ability to access the information entered into and processed by the TUD system is characterized by the fundamental wish to be able to utilize the information in the system to the greatest possible extent. This means that information must be available not only to the power companies which participate in the system via their power plants, but also to the suppliers, authorities and research institutions, etc.

The information supplied via the system is intended principally for internal use by the parties receiving it. The source must be acknowledged whenever the information is communicated more widely. In the event of the information communicated in this way identifying an individual reporting plant, then the approval of the contact person concerned must be obtained.

TUD organisation

TUD steering group consists of representatives from the participating companies Forsmark Kraft AB, OKG Aktiebolag, Ringhals AB and Teollisuuden Voima Oy (TVO). Swedish Radiation Safety Authority (SSM) is a co-opted participant. The representatives of the group are appointed by their own power company. An office at Vattenfall Power Consultant AB (TUD-office) operates TUD system. The office serves as a consultant to TUD steering group. A responsible TUD contact person is also available at each power station. The cost for TUD is paid by the four involved power stations.

For ongoing operation and maintenance and also development of the system the duties and responsibilities are divided between TUD steering group, TUD-office and TUD contact person at power station in a "TUD-manual".

Offshore database Oreda

Introduction

OREDA is a project organisation sponsored by eight oil and gas companies with worldwide operations.

OREDA's main purpose is to collect and exchange reliability data among the participating companies and act as The Forum for co-ordination and management of reliability data collection within the oil and gas industry.

OREDA has established a comprehensive databank with reliability and maintenance data for exploration and production equipment from a wide variety of geographic areas, installations, equipment types and operating conditions. Offshore sub sea and topside equipment are primarily covered, but onshore equipment is also included. The OREDA data are stored in a database, and specialised OREDA software and guidelines have been developed to collect, retrieve and analyse the information.

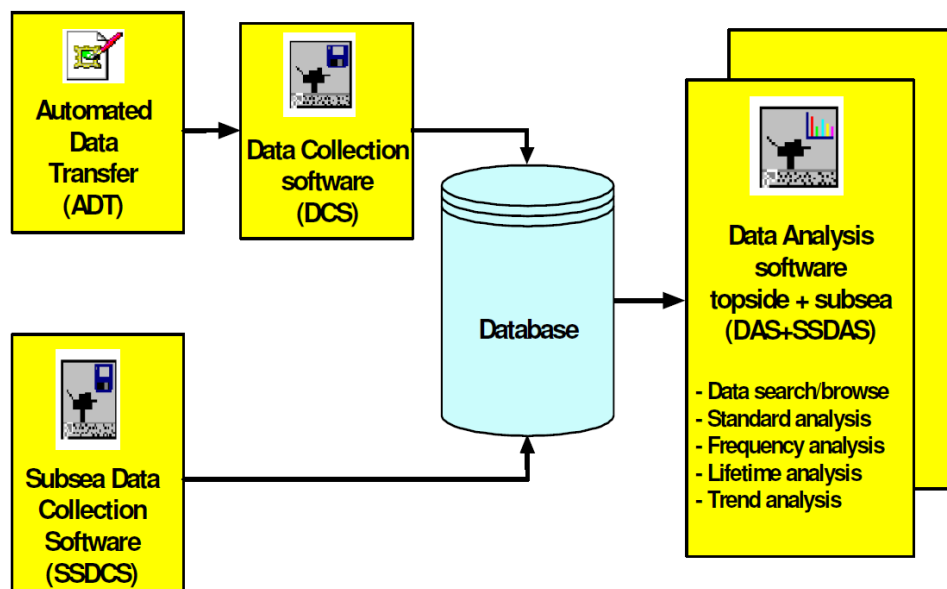


Figure 4: Oreda Software Modules

Input

The data comes primarily from the CMMS systems of the oil companies. There is no continuous transfer from the CMMS to OREDA database. As figure 4 suggests there is an "Automated Data Transfer" module, which can fetch data from the CMMS and "translate" to the data format OREDA requires. This is a semi-automatic process, where the oil companies themselves (or consultants they engage) must ensure the quality of data, and supplement with the necessary information that might not exist in the CMMS. As a result of OREDA an ISO standard for the collection of data (ISO 14224) was made. Most companies try to use this ISO standard when they configure the CMMS, but there is probably not 100% compatibility. OREDA database which in principle should be compatible with ISO 14224

would then not necessarily import completely correct data from the companies, therefore some manual work is required, and also quality assurance.

The principle of collecting is that OREDA steering committee regularly considers the need for more data, such as compressors installed on the seabed. When there is agreement between the companies who have such data, it is delivered to the OREDA database.

Component and failure data

The data are recorded per owner and installation. Each individual item (e.g. a gas turbine) occupies a single inventory record in the database. This record contains a technical description (e.g. manufacturer information) plus operating and environmental conditions.

For each inventory, all failure events are stored. Each failure event is identified by item name, date of failure, failure impact, failure mode, failure cause etc.

The maintenance records contain data on corrective maintenance linked to the corresponding failure record, and data on preventive maintenance linked to the corresponding inventory record.

The transfer of failure reports and inventory data from the sites to OREDA takes place in a common format. This is defined in a number of data collection guidelines:

Contents in the database

Topside/onshore data:

265 installations

16 000 equipment

38 000 failures

68 000 maintenance records

Sub-sea data from:

Almost 2000 well-years experience

Adriatic Sea

Guinean Gulf

Gulf of Mexico

Mediterranean Sea

North Sea

West of Africa

West of Shetland

Output

Output from OREDA can be used in 2 forms: Data handbook and system access.

Data handbook

One way to access data from OREDA is through the data handbook. The 5.th edition was published in 2009 and an excerpt is given in figure 5. This edition is divided into 2 books; one for topside equipment and one for sub-sea equipment.

Taxonomy no 13.1.9		Item Machinery Pumps Centrifugal Oil export									
Population 4	Installations 2	Aggregated time in service (10 ⁴ hours)						No of demands 480			
		Calendar time * 0.1018			Operational time † 0.0792						
Failure mode		No of failures	Failure rate (per 10 ⁴ hours).					Active rep. hrs		Manhours	
			Lower	Mean	Upper	SD	n / %	Mean	Max	Mean	Max
Critical		19*	121.72	186.12	261.04	42.80	186.58	14	45	23	90
		19†	144.86	238.62	351.32	63.30	240.00				
Breakdown		1*	0.04	9.67	36.47	13.45	9.82	18	18	35	35
		1†	0.06	12.21	44.87	16.57	12.63				
External leakage - Process medium		6*	0.35	60.50	214.15	79.09	58.92	8.6	16	11	16
		6†	0.44	81.27	291.26	107.62	75.79				
External leakage - Utility medium		10*	0.50	95.46	344.12	127.16	98.20	16	45	29	90
		10†	0.66	118.26	421.59	155.76	126.32				
Noise		1*	0.54	9.93	29.48	9.82	9.82	-	-	-	-
		1†	0.79	12.99	38.07	12.63	12.63				
Spurious stop		1*	0.04	9.67	36.47	13.45	9.82	8.0	8.0	8.0	8.0
		1†	0.06	12.21	44.87	16.57	12.63				
Degraded		12*	2.61	115.19	354.81	124.67	117.84	5.5	15	8.6	30
		12†	4.47	143.92	437.00	150.66	151.58				
External leakage - Utility medium		7*	7.90	67.69	176.19	55.26	68.74	4.7	15	7.1	30
		7†	13.04	85.56	211.15	64.53	88.42				
Vibration		5*	0.37	47.89	162.25	59.66	49.10	6.6	8.5	11	17
		5†	0.54	59.66	198.12	72.54	63.16				
Incipient		32*	100.04	310.91	616.58	162.23	314.24	3.4	12	3.7	12
		32†	152.50	395.56	731.12	180.34	404.21				
Abnormal instrument reading		25*	54.80	242.28	539.20	154.61	245.50	2.9	10.0	3.0	10.0
		25†	83.90	307.08	644.45	177.34	315.79				

Figure 5. OREDA data handbook excerpt

System access

The OREDA data are stored in a database, and specialised OREDA software has been developed to collect, retrieve and analyse the information.

If you have access to the database you can use the software for data analysis that is part of OREDA program. Then you can do more advanced searches, conduct various trend analysis, etc. There are also export opportunities, so you can import OREDA data into standard statistical packages.

Data analysis features

- Database content
- Failure rate/MTBF
- MTTR
- Failure modes
- Subunits/component failures
- Lifetime analysis
- Frequency analysis
- Export data/calculations

Access to information in OREDA

All who are not members of OREDA can purchase the data Book. But only those companies that are members of OREDA can utilize the database. In addition to the members who have access to data, companies can also give consultants access to data for a limited period to make analysis for companies.

Note that the data is anonymous. One company will see "their own data" non-anonymous, while the rest of the data are anonymous. Thus you can make "benchmarking" to compare with the others.

OREDA organisation

A Steering Committee (SC) comprising one member and one deputy member from each participating company manages OREDA. The SC elects one of its members as Chairman and appoints a Project Manager (PM). PM co-ordinates the activities approved by the SC including quality control of data.

DNV served as PM during phases I and II; SINTEF took over this role and served as PM during phases III-IX, before handing this role over to DNV again from 2009 when phase X was commenced.

There is an annual fee to operate the database and the members commit themselves to contribute their own data. The companies included pay/have paid a one-time fee.

Concluding discussion on similarities and differences

The databases TUD and OREDA have a lot in common.

A general weakness with OREDA, and some other databases, is that the "fixed position information" is poorly treated. In OREDA errors are reported in relation to the "Severity", there are three categories, C = Critical (carries out no function in accordance with requirements), D = Degraded (performs function, but the device is compromised in some way) and I = Incipient (the device has negligible deterioration). Thus, "Severity" is a rough indication of the state. But that's all. It would be desirable to have more detailed state information.

A similar argument is sometimes raised against TUD – not sufficient amount of detail to perform good maintenance-related analysis. The result is that RCM-related tools are introduced as a complement in the Swedish nuclear units.

One comment from OREDA is that two aspects from maintenance should be more focus on; WHAT to record (measurements, qualitative observations from inspections etc) and WHEN recording (preventive maintenance, corrective maintenance, control of state).

So one lesson that can be learned from this is that for maintenance-related work a lot of detail on observations and failure causes etc is needed. This is the kind of information discussed in the RCM-chapter above.

RAMS-database Wind. Alternative models concerning use and ambition

General

In the design of a database (system) there are a number of factors that needs to be identified and addressed. Below a number of such factors and possible solutions are presented and discussed. Advantages and disadvantages with possible choices are listed and some recommendations are made.

Capability of the database – user

A brief description of a CR-database is given above. Some more discussion of this is needed.

At first a discussion of purpose. What are the main possible uses/users of such a database?

- Maintenance organisation and maintenance optimisation
- Construction/design purposes
- Purchasing optimisation
- Operational optimisation
- Investment calculation, support for investment decisions
- Others?

a) Maintenance optimisation

The maintenance organisation and people working in order to optimise maintenance are one possible user group.

- Discussion
Much effort in many parts of the Power Industry (and elsewhere) is put into the maintenance sector today. The idea is that economy and many other reasons point in favour of a good maintenance. This is valid for the Wind Turbines as well. Good maintenance is often mentioned as a priority in the years to come. RCM is an acronym often used relating to good maintenance. In order to achieve this, good information is needed and a CR-database would be a major source of good information.
- Conclusion
Maintenance optimisation is one major use of a CR-database.

b) Construction/design

The construction/design organisation is another possible user group.

- Discussion
A lot of money could be saved by designing the equipment according to gained experience. Information from a CR-database would be very valuable to make decisions on what to use and what not to use.
No (or minor) special types of information needed for construction purposes so a database designed for maintenance needs is sufficient for designers.
- Conclusion
Could make important use of a CR-database. No special needs compared to maintenance needs.

c) Purchasing optimisation

The purchasing organisation is another possible user group.

- Discussion
A lot of money could be saved by purchasing the right equipment. Information from a CR-database would be very valuable to make decisions on what to buy and what not to buy. No (or minor) special types of information needed for purchasing purposes so a database designed for maintenance needs is sufficient for purchasing.
- Conclusion
Could make important use of a CR-database. No special needs compared to maintenance needs.

d) Operational optimisation

Optimisation and improvement of operation could be a purpose.

- Discussion
Probably all information needed for operational purposes is already available or not related to a CR-database.
- Conclusion
Not expected to be a major user of such a database.

e) Investment calculation, support for investment decisions

Information needed for investments is one possible use.

- Discussion
Major investment normally do not use low-level information on components. If they do, information can be supplied by maintenance department.
- Conclusion
No (or minor) special types of information needed for investment purposes so a database designed for maintenance needs is sufficient.

Conclusion

Main expected use is related to maintenance optimisation. All other users can use the "maintenance information".

The need of a CR-database for other purposes than maintenance is probably not sufficient to motivate the resources required to design and operate it (statement based on common-sense).

Capability of the database – output

Previous chapter ends in a conclusion that maintenance organisation is the main expected user of a CR-database. Some other users are also possible assuming that maintenance information is collected.

What is the main output from such a database?

a) Generate reliability data

The basic reliability data needed are

- MTBF/ failure rate for components. Total and distributed on failure modes etc.
- MTTF/ repair time for components. Total and divided into parts such as waiting times.

Capability of the database – criteria for usefulness

In order to make efficient use of this potentially vast amount of data some criteria could be the following:

a) Possibility to select a precise component or group of components

It must be easy for a user to select one specific component or to create groups of components consisting of components which are similar, as defined by the user. Also included in the selection criteria should be all operating, environmental, etc criteria existing in the database. As an example the group can consist of pumps between 1kW and 5 kW located in off-shore units and made by supplier A. For the desired group the user can generate reliability data (defined above). The more flexible – the more useful.

b) Possibility to select desired time frame

It must be easy for a user to select a suitable time frame. As an example compare the above selection of pumps for years 2010–2011 to 2012-2013. The result from this shall be MTBF for example during the 2 periods in order to see if there is a difference.

c) Good statistical tools

The possibility to use good statistical tools may be very helpful. If there are few observations of a specific failure mode it may be helpful to use statistical measures. Bayesian techniques can assist to extract useful information from rare data points. To give one example – only 1 failure of a certain component and a certain failure mode has occurred. This is difficult to draw conclusions from. But if we know that similar components have had 35 failures in this same failure mode then we know something more which can be helpful provided we have tools to relate these 2 facts to each other.

d) Graphical output

This is not a criteria but very useful.

If the result can be produced as graphs then trends are very informative.

Also the selection of components may be helped by a graphical interface (outside the scope of this report but important).

Coverage

What should be the coverage and what are the consequences of different coverage?

What are the scopes to select?

- National (Swedish) – international
- Limited to certain sizes or not?
- Limited to new types only?
- Limited to certain suppliers or not?
- Limited to certain designs or not?
- Limited to certain localizations or not? On-shore – off-shore for example
- Others?

a) National Swedish coverage (compared to international)

The equipment covered by the CR-database is limited to Wind Turbines in Sweden. All the formats, reports etc are made in Swedish. If the database is international it would mean either that texts and some other information would have to be in English in the CMMS or that translation procedures must exist.

- Advantages (with Swedish limitation)

Simpler for the Swedes involved, to read and write everything in their native language. This may contribute to a better quality in such things as free text, if this exists.

Could be more simple to relate to incentives such as specific national rules or "elcertifikat".

- Disadvantages

Seen from an operator point of view it is very inconvenient to have different reporting for units localized in Sweden, Norway, Finland, UK etc. A major advantage for a large operator is to have a common reporting and experience feedback.

In a reliability database it should be interesting to compare equipment in different environments, such as maintenance, weather, .. A national restriction will reduce this input and usefulness.

- Conclusion

For a reliability database to work well is it probably critical that it supports the interests of some major operators or stakeholders and for those an international scope is vital, probably a condition to participate.

b) Limited to certain sizes (compared to not limited in sizes)

The equipment covered by the CR-database is limited to Wind Turbines larger than X MW.

- Advantages

There is a large number of smaller units but the larger operators/utilities mostly focus on large units. The reliability characteristics might be different for small units compared to larger ones. To focus on the larger units might help to avoid misleading information related mostly to the smaller units.

If main interest is with larger units it might not be worth the money spent to handle information for smaller units.

- Disadvantages

If the reliability characteristics are depending on size it should be interesting to have better information on this. The best way to accomplish this is to gather the information in a common system.

To have one system/database for large units and another for smaller seems inefficient.

The larger units have been in operation for a shorter time and some are still under warranty.

- Conclusion

It is likely that major operators are mainly interested in large units so the focus of a reliability database should be those large units but there should be no absolute limit in sizes. A desirable situation would be if all/most large units are reported to the database and a number of the smaller units also. It could be up to the data suppliers to decide which of the smaller units should be reported.

c) Limited to new types (compared to not limited in types)

The equipment covered by the CR-database is limited to new types of wind turbines.

- Advantages

There is a cost for operating a reliability database and feeding information into it. A cost-benefit approach could mean to focus on equipment where you have most to learn. This

applies of course to new types rather than existing units where there is experience and knowledge already.

- Disadvantages

For improving maintenance we need better information than we have today so even older units should be included in order to lower operating cost.

- Conclusion

The database should not be restricted to only new types.

d) Limited to certain designs (compared to not limited in designs)

The equipment covered by the CR-database is limited to certain designs of wind turbines.

- Advantages

There is a cost for operating a reliability database and feeding information into it. A cost-benefit approach could mean to focus on equipment where you have most to learn. It could be argued that we know a lot about certain types and less about other so there is more need for information related to certain types.

- Disadvantages

For improving maintenance we need better information than we have today so all existing units should be included in order to lower operating cost.

- Conclusion

The database should not be restricted to only certain designs.

e) Limited to certain suppliers (compared to not limited in suppliers)

The equipment covered by the CR-database is limited to Wind Turbines from certain suppliers only.

- Advantages

By restricting the content the database will be more uniform and easy to handle.

This might improve cooperation with the suppliers involved and they can contribute with information that only they possess.

- Disadvantages

One advantage with a reliability database is the possibility to compare alternative equipment and if there is a restriction on suppliers the possible comparisons will be fewer.

- Conclusion

The database should not be restricted to only certain suppliers.

f) Limited to certain localizations (compared to not limited in locations)

The equipment covered by the CR-database is limited to wind turbines for example offshore or possibly only on-shore.

- Advantages

Equipment offshore may have reliability performance different than on-shore. So if the effort is concentrated to offshore we can avoid being misled by behaviour only relevant for on-shore.

- Disadvantages

One advantage with a reliability database is the possibility to compare alternative environments and if there is a restriction on environments the possible comparisons will be fewer.

- Conclusion

The database should not be restricted to only certain localizations.

Taxonomy

A common designation system or not?

One important aspect is how to name and structure the equipment handled by the database. All equipment needs to have an identity such that it is unique and describes the relation to other equipment.

All suppliers have such a system, normally unique for this supplier. It is not always easy to compare component abc in wind turbine A to component def in wind turbine B since the designation system may differ.

How can this be handled in this type of database? In TUD, described earlier, this is solved by storing the original supplier designation and also an "Object code" with subgroups decided by TUD and common to all.

What are the criteria which must be fulfilled by a system for structuring information?

A described component designation should:

- be unique.
- clarify the relation between one component and all other components on site
- make possible to identify components with same "role" in different units.

Today there is a system which seems to be a de-facto-standard or will be. Vattenfall has decided to use RDS in all countries and so has Statkraft. RDS is not yet fully implemented by the utilities but will be within a few years. In the working group for RDS, participants come from Vattenfall, Eon, RWE as well as others. EPRI in USA also mentions RDS/KKS as the system to use. Some manufacturers are moving towards RDS, for example Siemens and Enercon. So RDS will probably be the most common in the years to come.

Reference Designation System RDS-PP (Power Plants) is a successor of the mainly German system KKS. RDS-PP exists for gas, hydro, wind etc. D2 is related to wind. RDS-PP operates with 3 aspects - function aspect, product aspect and location aspect.

- a) One possibility is to use the RDS as a common system for identifying all components.
- b) Another possibility is to use a total "functional breakdown" used by RCM (Reliability Centred Maintenance).
- c) The third possibility is, as in TUD, to use the designation system used by everyone supplying data and to use some kind of translation to a common description.

The RDS-standard is under revision (2010) and will contain more examples, today it is possible to make some interpretations according to your own wish on how to use it. The scope will also be increased to contain surrounding equipment such as transformer and export cables from an offshore park.

a) Use RDS as designation system

RDS is used as the taxonomy in this alternative. If there are wind turbines who cannot supply RDS information a translating software is applied on all data going into the database. The new designation system is based on international standards, especially to DIN ISO 16952-1, DIN EN 61346-1 and IEC/PAS 62400, related to the structuring principles and the designation systematic. The VGB Working Panel "Reference Designation and Plant

Documentation“ takes an active part in the development of the RDS-PP and its underlying national and international standards.

The international harmonization of the RDS-PP and its constant structuring help to avoid errors and misunderstandings during the designation whereby the plant reliability is increased.

RDS-PP is - same as the KKS - a common standard for operators and manufacturers of power plants. The worldwide accept opens further potential for long-term cost reductions when planning, construction and operating of power plants.

- Advantages

The criteria above are fulfilled.

As RDS seems to be a future standard it is advantageous to use it early.

- Disadvantages

In the early stages some turbines may not yet be named according to RDS and a translation may be needed.

Some operator may decide not to use RDS which will increase the effort to translate.

- Conclusion

Natural solution for the future. Some initial problems may occur.

b) Use RCM Functional breakdown as designation system

Functional breakdown is a normal procedure in RCM to define the objectives of maintenance in terms of user requirements.

If the goal is to create an integrated CR and RCM database, all functional failure and failure modes must be created in advance by all stakeholders, which is difficult to do.

If CR and RCM are separate databases there is no need to have a RCM functional breakdown in CR. In this study we assume that the CR database is completely independent of RCM.

(RDS contains an aspect Functional aspect which is not discussed here.)

- Advantages

The database output will be very easily used for RCM-purposes.

- Disadvantages

Different functional breakdown may need to use for different types of wind turbines if their functions are not the same.

All stakeholders must agree on and define functions etc. in advance which can be difficult.

- Conclusion

Use only the RDS as designation system in CR database.

c) Use individual supplier system as designation system

The designations used for each wind turbine is used and imported into the database. In addition to this the database contains a common designation standard, which could be RDS, and all components are classified both with the “home-designation” and the common designation.

Some manufacturers/utilities are starting to use RDS as designation system.

- Advantages

Simplifies the transfer of data into the database. The users will be more familiar if they can use designations they are used to.

- Disadvantages
Difficulties to compare between units.
- Conclusion

This is a more simple solution but not as good as the RDS-solution in the long run.

Individual follow-up

One way to perform a Component follow-up is to record a specific position. This is how TUD works. All failures etc occurring in one position will be recorded. For example failure in a valve is recorded and if the entire valve is replaced with another there is still one failure in the valve position. The failing component may be taken to a workshop and repaired and then put into use in another position. TUD does not follow this specific component but the position.

It is also possible to have a system which traces the specific components. This is called here individual follow-up. Modern CMMS are able to handle this.

In RDS this aspect is covered as "Location aspect". Each component may be assigned an individual number and then it can be followed as to which turbine it is located.

a) Individual follow-up

The main components are followed both on position and through its different positions. It is possible to see failures in a specific position but also failures in a specific individual which have been working in more than one position. An individual may be defined as "a component which is profitable to repair".

- Advantages
Weak specimens may be much more easily spotted. There may be "Monday-components" with a significantly worse reliability performance than the others. There might also be groups of "bad series" which can be identified.
There is a study within Vattenfall Vind/VPC concluding that in general it is profitable to repair "components" rather than dismantle. (This is a big discussion which does not have to be considered here.) In order to make full use of repaired components You need to know where they can be used and also where have they been used. (This is a task of a CMMS.)
It is more difficult to add such a functionality afterwards, it should be from the start if desired.
- Disadvantages
Takes a bigger effort to achieve. If the source of the information is a CMMS then component identification information must be recorded and followed in this CMMS in order for this to work. If the source is a manual failure report it is some more figures to write. This is not a software aspect, it is only related to the access of such information.
- Conclusion
This is very interesting information but it takes more resources to collect.

Failure data codes

For each failure it is highly desirable to know more than the fact that a component fails. How much more?

For each failure a failure report could contain for example the same information specified in Table1 from TUD.

One aspect that is sometimes discussed is whether a failure should be described by predefined codes or by only plain text.

a) Predefined classes

The reporting format, in the CMMS or in the special form, contains predefined classes which have to be (should be) filled. There is also room for free text.

- Advantages
This is needed in order to get information on what type of failure occurred, what effect it had, action taken and reason for failure. Predefined classes makes it much more easy to treat statistically instead of free text which does not work well with statistical tools.
- Disadvantages
Sometimes it is argued that it is better to use only free text since the groups are too rigid. Free texts can be sorted with software tools.
- Conclusion
Use of predefined classes is recommended

b) Free text

Description of failures are given only by free text. No classes.

- Advantages
Gives more room for the service people to describe the situation.
- Disadvantages
Everyone will use his/her own expression. Difficult to treat statistically. Has not been successful where tried.
- Conclusion
Not recommended.

Access to information

One aspect that must be very early defined is who will be able to access the information in the database and in what form and level of detail.

A general statement and basic rule is that each supplier of data to the database is the owner of this data and can access this data in any format that the software provides. But more then this, how can each supplier (of data) have use of information from the other suppliers? From an IT-technical point of view there is no problem to limit access to according to the needs. The point here is who should be allowed.

a) Each data supplier can access only his own information

Hard restriction so that no one can see anything else than his own information. If some comparison with others is desired he will have to ask another data supplier for this information.

- Advantages
No problem with competition. No need for data restrictions on the part of the data supplier.
- Disadvantages

Does not make full use of the fact that a large amount of data could be used to compare “us” to “them”.

- Conclusion

Not a recommended solution.

b) Each data supplier can authorize another data supplier to access it also.

By agreement stakeholder A and B can agree to share information.

- Advantages

No need for data restrictions on the part of the data supplier.

- Disadvantages

Still does not make full use of the fact that a large amount of data could be used to compare “us” to “them”.

- Conclusion

Better than “single-access” but still not a recommended solution.

c) The operator of the database performs general comparisons

Each data supplier gets generic, unidentifiable data to compare with his own data. It should not be possible from this to see suppliers or individual units.

- Advantages

Makes full use of the large amount of data in the database.

- Disadvantages

Some data supplier may feel this restricts what he should transfer to the database.

- Conclusion

Recommended solution. Necessary to define precisely the forms for this.

d) Each supplier can access all information in the database.

No restriction at all for those who supply data.

- Advantages

Makes full use of the large amount of information.

- Disadvantages

This will probably restrict transfer of data to the database. An operator does not always feel that all information should be accessible to their competitors.

- Conclusion

Not a recommended solution.

e) Organisations not supplying data can request information

The operator of the database can decide how to handle requests. In general it could be OK to give generic information for research and manufacturer detailed data to the manufacturer.

- Advantages

The information is valuable and should be used.

- Disadvantages

Restrictions needed how to do it.

- Conclusion

Recommended but rules must exist how to handle requests.

Sources of data

The information for such a CR-database can basically be supplied from 2 types of sources; either from other computers or from manually written forms. There can also be many combinations of these 2 but below is discussed the 2 “pure” extremes.

a) Information supplied by other computers

The basic information needed for a CR-database exists in CMMS. This information is used and if needed the formats etc is changed before transferring to the reliability database. If other information such as wind-speed, operating status etc shall be included this is transferred from other computers where it exists.

- Advantages
 - Simple and cheap.
 - Good data quality. No-one needs to supply the same information to 2 computers.
 - Only one piece of data exists. There will not be conflicting data for one specific fact. A point in time will be the same in the CMMS and in the reliability database for example.
- Disadvantages
 - May cause some initial problem to define transfer and also some IT-problems related to software changes later but these are minor.
 - Does CMMS exist for all wind turbines? Who has access to this information? Today suppliers have a large part of this information and the operators do not or only with restrictions. However this will change as warranty periods end and as new units are purchased under new agreements.
- Conclusion
 - Recommended solution but perhaps with some minor manual data input.

A statement: a CR-database should only be operating for wind turbines where information from CMMS can be used. If a reliability database is decided/supported this should also mean that conditions for transferring data are set by necessary agreements where needed.

b) Information supplied by manual reporting

All information in the database is produced by manually filling special forms, on paper or computers.

- Advantages
 - Easy to start the reporting procedures. No need for computer interfacing or local arrangements.
 - Reporting information may be precisely adapted to the needs of a reliability database.
- Disadvantages
 - In the long run more costly than the computer solution.
 - Quality may be harmed if repair crew are expected to fill the same information to 2 computers and 2 systems.
- Conclusion
 - Not a recommended solution.

c) Continuous flow of data

The data continuously collected and transferred. It may be transferred with intervals but all failures occurring are reported, not only those occurring during special reporting periods. Example TUD which works like this.

- Advantages
All history is recorded, not only occasionally.
- Disadvantages
No real disadvantages
- Conclusion
Recommended solution since it gives a more complete information at a cost which in the long run should not be higher.

d) Data collected in campaigns

Data collection takes place on special occasions such as “this year we will collect information from units A1-25 and next year B26-50”. Example “German TUD” – reliability for German nuclear units.

- Advantages
Possibly somewhat cheaper
- Disadvantages
Only pieces of the history are recorded.
Difficulties in starting the collecting routines will occur every time a start-up is performed.
- Conclusion
Not recommended.

Economic aspects

A lot of information exists that would be interesting to include. Should the database include economic factors?

a) Economic factors included

The database records information about production losses (SEK, Euro, etc) due to failures, cost of spare parts, price of repair crew, ...

- Advantages
Such information is easily accessible.
Maintenance efforts can be optimized on economic information.
- Disadvantages
Economic information varies depending on many factors such as for example production of hydro power. The information may not be relevant for future situations.
The database discussed here is assumed to include information from several operators and they often regard economic information as restricted. This may mean that economic information may not be supplied and this may also mean that some other factors also are not transferred to the database. The result could also be that some stakeholder says they are not interested to participate if economic factors are included in the scope.
- Conclusion
Pure monetary factors should not be included. Resources, however, such as for example 2 people working for 1 hour, is discussed elsewhere.

Component data

In order to be able to calculate reliability figures such as MTBF it is necessary to know how often a component fails but also how many components there are. So equipment data is needed. The more engineering information there is, the more useful the database. So finding the right level of detail is important.

a) Component data

The number of components and some detail on each component exists in the database.

- Advantages
Necessary in order to be able to use the failure data for meaningful estimates.
- Disadvantages
 - Will need some effort to generate and keep up-to-date.
- Conclusion
Necessary. Level of detail discussed below.

Level of ambition

This subject is central and important – how much detail should be in the database? The more detail – the more real information can be found but also the more detail – the more effort needed to collect data.

a) Equipment detail, low

A low level of detail could mean that for example "Gear box" is identified as a basic component. The reliability performance of all gearboxes can be traced. The alternative is to have more details.

- Advantages
Cheap and simple data collection.
- Disadvantages
Not possible to see what the problems are with the specific gearbox. You will have a failure rate and possible failure modes. From the free text you may be able to draw some conclusions. It will not be sufficient information for RCM or other maintenance support.
- Conclusion
Not a good alternative if the information shall be used for RCM (or similar).

b) Equipment detail, high

A high level of detail would mean that components are traced down to the lowest level applied in the CMMS. The reliability performance of all replaceable parts can be traced. The alternative is to have less detail – see above.

- Advantages
This is the level of information needed for RCM (or similar technique).
- Disadvantages
More effort needed to collect data.
- Conclusion
Recommended for reasons of RCM.

Manufacturer information

For each component the manufacturer is identified. Thus it will be possible to compare manufacturers/brands.

- Advantages
Highly interesting information. To know that this component from supplier A fails more often than the similar component from supplier B is very interesting. If the components are made with different technique then this might also be an indication that technique B is better than technique A.
- Disadvantages
Manufacturers may disapprove of this and try to restrict this kind of information. They might be more negative to participate in such a database project.
- Conclusion
Better information balanced against acceptance of database from possible shareholders.

Operating, environmental etc data

What other information could be interesting? Some factors are listed here with comments.

Availability

It is interesting to know the status of the unit in terms of availability and also production. This information exists and could be transferred from existing computers.

- Conclusion
Recommended.

Maintenance information

A lot of maintenance information, such as for example preventive maintenance and diagnostics made recently, exists and "could be interesting". However this could mean a lot of information and could mean difficulties setting borders what to include, etc.

One important aspect is maintenance interval of the component. In its most simple form the present maintenance interval. With a higher level of ambition the history of maintenance interval is included. For example this means "Preventive Maintenance was performed 2 times a year during the first four years and after that up to now once a year". For maintenance optimization purposes this is valuable information performing RCM.

Measurements from status-checks can be considered for certain components. Depends if it exists in a computerised form.

- Conclusion
Maintenance intervals recommended including its history. For certain components some additional maintenance information might be relevant to include.

Operating conditions

There is also a lot of potentially interesting operating information as

- Wind speed at the time of the failure
- Temperature/humidity
- Wind direction
- Turbulence

If this exists in a form which can be easily transferred it certainly could be of interest, perhaps especially the wind speed.

- Conclusion

If possible to transfer the wind speed at the time of failure this should be recorded in the database. Not the other factors since direction and turbulence are very local information. Temperature might also be sufficiently important, for example from an icing perspective.

Distributed database

A database could be designed as a distributed database where a limited part of the data actually is stored in a central location. The rest of the data could exist locally for example in CMMSs or in other computers and accessed only when calculations are performed.

This is quite possible to achieve but is not discussed here since this is mainly an IT-related issue which falls outside the scope of this report.

Summary & Conclusion

General

In this paper some possibilities are recommended, some are not and some are recommended "if...". The idea here is to present two possible levels where level 2 is the more ambitious approach. Level 1 is not sufficient information for RCM.

Recommendations common to both levels

Scope: international (mainly European) coverage

Scope: not limited in size (but focusing on >X MW)

Scope: no limitation on type, design or supplier

Taxonomy: RDS used as a designation system

Failure data: Predefined classes

Access: own detailed data plus generic data.

Source of data: CMMS in a "continuous" flow

No economic data

Availability and production information included.

Level 1

No individual follow-up

Equipment detail, low

No manufacturer information

No operating conditions

Level 2

Individual follow-up

Equipment detail, high

Manufacturer information included

Operating conditions: wind speed and temperature at the failure

Extension

It is possible to start at level 1 and later expand data input to level 2 if this is foreseen from the beginning.

The exception from this is individual follow-up which probably will be difficult to include afterwards. This should be included or excluded from the beginning.

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Importance of reliability data analysis to estimate the parameters for the maintenance optimization of offshore wind turbines

Zafar Hameed¹, Stefan Faulstich², Jørn Vatn¹

¹Norwegian University of Science and Technology, N-7491 Trondheim, Norway

²Fraunhofer Institute for Wind Energy and Energy System Technology, Kassel, Germany

E-mails: zafar.hameed@ntnu.no

Abstract

Renewable energy has started to emerge as an alternative source of energy to traditional fossil fuels due to their depletion and detrimental impact on the environment. Wind is an important source of renewable and its share in the market has started to increase on a rapid scale. The viability of wind energy heavily depends upon the design and operations at the same time as both are intertwined. To make the operations efficient and cost effective, condition monitoring systems are installed on the wind turbines to collect the reliability data. The collection and analysis of the data to estimate the reliability parameters carry fundamental importance in maintenance and operation planning of wind farms. This paper discusses what kind of reliability parameters are needed in the planning and optimization of maintenance and operation. Basic parameters like average failure rates are relatively easy to obtain from available raw data, but parameters in aging models and condition based models are not easily obtainable. The paper gives an overview over relevant databases for wind reliability data and which parameters can be obtained. A case study where several statistical methods are applied on one of the available data sources is presented. A method is proposed to modify reliability parameter estimates obtained from onshore wind turbines to such offshore installations.

Keywords – Reliability, data analysis, failure rate, maintenance

Introduction

Data collection plays an important role in maintaining and enhancing the reliability and maintainability of the wind turbine systems especially rotary equipment. There are number of ways to gather such information by conducting experimental work and installing condition monitoring systems (CMS). Based on the information collected, the data is processed to undertake the diagnosis and prognosis to estimate the state and the technical health of the system. The results of such analyses heavily depend upon the quality and the sampling frequency of the data. More over the chosen method plays an important role in extracting valuable information out of the available data for estimating and predicting the health of the system. In short, there is no substitute for acquiring real data from the on-going equipment

for enhancing their reliability and maintenance and then predicting their availability levels for their intended output.

With the emergence of wind turbines in the energy market from last three decades, lot of emphasis has been put on measuring and collecting the related information for estimating the current operational states at the assemblies, subassemblies and components level. For this purpose suitable architectures of CMS were designed and installed on the wind turbines for gathering valuable information in order to conduct different kind of analyses. An overview of such aspects is given in detail by [1, 2] regarding what kind of methods could be employed for enhancing the reliability of wind turbines and the issues in the design and installation of CMS for wind turbines.

From last decade, the focus has been shifted from onshore wind turbines to offshore units due to a number of technical factors like higher wind speeds around sea as well as due to social reasons like people do not like to see land based energy systems around their vicinity. This trend has generated good prospects but has also posed new challenges how to ensure the reliability of such units compared to onshore. It is important to note that less information is available regarding how the wind turbines are expected to behave in marine environment. How the maintenance and inspection strategies are going to be planned and implemented due to the weather window, access and logistics constraints. All these issues need thorough investigation which demands to devise methods and ways to translate experience from land based wind turbines to offshore units.

It is important to know how the reliability and availability levels achieved for land based units could also be achieved for offshore wind turbines to make them more viable and attractive for the investors. One possible solution is to use reliability data available for onshore units to analyse their behaviour and then to devise strategies to map such information to offshore installations. The translation of this experience from one environment to another is not straight forward. To overcome this challenge, a method is proposed where it is described how the necessary parameters for maintenance optimization could be extracted after conducting analysis. Furthermore, it is outlined how to map the information from onshore wind turbines to offshore units keeping in mind the entirely different working environment for both types of machines.

In the coming section, an overview of reliability data bases, both from wind and other industries, has been succinctly described. The main components of the proposed method are outlined in the next section. Then the results are summarized before going to the conclusion section.

Reliability Database

With the installation of wind turbines, the data collection was started to analyze the failure rates and their causes to plan and optimize the maintenance strategies. For this purpose, condition monitoring systems (CMS) were designed and integrated in the wind turbines to get continuous feedback from the operational behavior. Based on the operational data, strategies were devised to conduct preventive replacements and in case of sudden failure to

fix it under the corrective regime. The data related to the frequency of failures and accompanied downtimes was also collected to optimize the visits to the wind farm.

On a broader scale, the organization and classification of a reliability database should fulfill the following objectives:-

- Collection of failure statistics and accompanied corrective strategies
- Calculation of the loss of production due to failures and repairs
- Optimization of the design process based on the operational feedback
- Determination of expected period of pay back on the investment

For improving and achieving higher levels of reliability, numerous databases were established across Europe, USA and other countries. Few of them are briefly described here:

- WindStats Newsletter: The WindStats Newsletter was established in 1987 and since then it is serving the wind industry. The partners of it are American, European, Danish, British and Canadian Wind Energy Associations. It has published the latest trends in the wind industry in addition to publishing the production, failure and maintenance related data. It gives information about the production capacity of wind turbines on a monthly and a yearly basis. The root causes of failures are given for the main components of the wind turbines in this database.
- VTT wind database: The VTT (Valtion Teknillinen Tutkimuskeskus) database was established for the wind turbines installed in Finland. The database contains important information about failure rates, downtimes and failure causes. The distribution of failures rates and their causes are based on different wind turbines subsystems. Based on such analyses it was found out that the hydraulic system has the highest share in the failure rates among the wind turbine components. In terms of downtime, gearbox, hydraulic system and brakes were the most important systems respectively for interrupting the production in case of failure. Due to its climate conditions, the icing was an important cause of failure for the turbines installed in that country.
- WMEP: The “Scientific Measurement and Evaluation Programme (WMEP)” database is launched and managed by Fraunhofer IWES Kassel Germany. It contains information about failure rates, their cause, the adopted maintenance strategy and the duration of time for the completion of this activity. It was found out that vibration was one of the main causes of failure among different wind turbines manufactured by different companies. The data for the wind turbines was collected from different locations in Germany which may prove helpful to analyze the viability of the certain location for exploiting wind by installing turbines there. WMEP version was related with onshore wind turbines and now a new version of the same database for offshore wind turbines, which is called Offshore-WMEP, is about to be launched soon. It will be an interesting analysis to evaluate how the failure rates, their causes and

maintenance actions will be different from those being compiled in the land based reliability database.

- **OREDA:** The OREDA (Offshore Reliability Data) is mainly dealing with reliability issues in the oil and gas industry in sea environment. This is one of the first established reliability databases with several member countries like Norway, Netherland and others. The information regarding the failure rates, their causes and man hours consumed for fixing the problems is collected from pumps, gearboxes, valves and other such equipment which are installed in the offshore oil and gas platforms. Based on this database, plenty of improvements were carried out in the design of new equipment which shows significant benefit of being a part of such activity. The experience from this database is directly relevant for the new such initiatives like Offshore~WMEP to translate expertise from it. That is the main motivation to briefly describe about OREDA here in this piece of writing.

Some of the important databases are briefly described to give the reader a glimpse regarding the significance and need of gathering the reliability database. There are other databases in wind industry like LWK (Landwirtschaftskammer Schleswig-Holstein), Garrad Hassan etc., and others are in the proposal stage especially for offshore wind turbines. It is an interesting fact that other industries have also established reliability database especially in the nuclear and aeroplane sectors like TUD and SAAB respectively.

Method

The reliability database for onshore wind turbines is an established field across the work to gather information from the given wind farms for the estimation of overall efficiency. But there are certain social and technical issues coupled with those land based wind turbines like close proximity to residential areas, damage of local landscape, negative psychological impact on the persons living around those units, and less availability of wind speed compared to the same at sea. Such kinds of problems have compelled the investors and companies to think serious to address these concerns. One possible solution proposed is to shift wind turbines into the shallow and deep sea waters for exploiting maximum wind potential available there and also to appease the local public.

The shift from land to sea has provided opportunities but still at the same time, created new challenges which need our attention. One of the challenges is to estimate and ensure the availability of wind turbines in sea for making that alternative a feasible one. The availability of any wind turbine is directly coupled with the achieved reliability and maintainability levels. This is a gigantic task due to the paucity of information available at hand to understand the behavior of offshore wind turbines (OWT). Up to now no established reliability database is available for OWT as it is there for the land based units. There are number of initiatives proposed by IWES, ECN and other such organizations but still they are under progress. If there is no reliability data regime for OWT available, then what should be the alternative?

The question comes in mind which forces us to address this issue based on the existing resources and expertise.

Keeping in view these issues, a procedure describing how to estimate reliability parameters for OWT based on the information available from land based turbines is presented here. It is worth mentioning here that this is not an easy task due to the change of operational environment from land to sea combined with the concomitant change of wind turbine design. E.g. the estimation of reliability parameters may prove difficult due to the presence of marine currents, wave height and marine creatures. So by considering all complexities, an attempt has been made to structure the procedure in such a fashion to make the results as close to reality as possible.

The main steps of the proposed procedure are highlighted below:

Step 1 Estimation of initial failure rates

At the starting point, it is important to investigate the failure rate λ with respect to the relevant failure causes. There is a need to know that when the failure was occurred due to a certain cause, then what kind of measures were adopted to lower the impact of such abnormalities on the system's performance. So the first step is to decompose the generic failure rate in such a way to quantify the contribution of each failure cause as under:

$$\lambda = \lambda_1 + \lambda_2 + \dots + \lambda_n \quad (1)$$

where the index $i = 1, 2, \dots, n$ runs through the n different failure causes, being responsible for the malfunctioning of wind turbine' assemblies and subassemblies. Some of the possible failure causes are vibration, wear out, misalignment, icing, lightning etc. The information regarding the most important n failure cause may vary from one database to another due to the different operational environment. So failure causes should be determined based on the particular location. The VTT database for example showed icing is one of the important causes of failure due to the arctic environment but in WMEP database, vibration is the critical factor for malfunctioning. In short, the decomposition process done for one database may not be valid for another one.

Step 2 Analysis of failure causes

After the decomposition process, each failure cause needs to be analysed with respect to the performance of the wind turbine assemblies, subassemblies and components. For this purpose, FMECA (Failure mode effect and cause analysis) could also be conducted to analyse the impact of failure causes by quantifying their impact on the performance. A higher impact of a failure cause on the system has a higher severity level which should be accounted through an appropriate importance in the analyses. It is important to analyse what kind of measures have been adopted to eliminate the impact of such failure causes.

Different failure causes are responsible to determine the types of failures and their impact on the system performance will tell about the nature of aging effect. When dealing with failure causes, it is important to differentiate between the independent and dependent nature of failures based on the given failure causes. When the failures will be divided in such categories, as shown in Figure 1, then we have to introduce a measure say β to measure the degree of this dependency being responsible for the failure λ . The components which are failed due to independence could be given as $(1-\beta)$. All this could be translated by modifying equation (1) as under:

$$\lambda = (1-\beta)\lambda + \beta\lambda \quad (2)$$

$$\lambda = \lambda_{Independent} + \lambda_{Dependent} \quad (3)$$

For a given cause of failure, the independent and dependent failures will be quantified by using equation (2). It is important to estimate the parameter β which is reported in the literature as Beta factor model and first introduced by [3] where it has been laid down how to calculate it. There are certain shortcomings associated with beta factor model like it gives equal weight to different achieved redundancy levels of KooN. For example 1oo2 and 2oo3 configurations will get the same PFD (probability of failure on demand). To address its shortcomings, PDS [4], was introduced which was based on multiple beta factor model. There are also other methods to quantify β factor like C-Factor [5], Multiple Greek Letter (MGL) [6, 7].

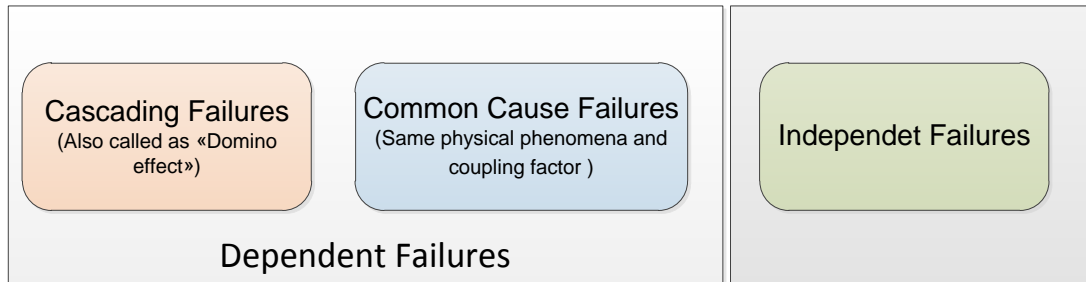


Figure 10: Failure classification based on the initiation causes

Independent and common cause failures (CFF), a type of dependent failures, are treated in equation (2). There exists another class of dependent failures which is called cascading failures. The cascading failures [8] are multiple failures initiated by the failure of one component in the system that results in a chain reaction or “domino effect”. When several components share a common load, failure of one component may lead to increased load on the remaining component and consequently to an increase likelihood of failure. Cascading failures are analyzed by using the Event Tree Analysis technique by measuring the impact of certain events on the overall operations of the system. The cascading failures are quantified by the rate of occurrence of an event say $w(t)$ which will results in the system failure while going from t to Δt as under :

$$w(t) = \frac{\text{Mean no. of failures in } (t, t + \Delta t]}{\Delta t} \quad (4)$$

Thus the mean number of failures in $(t, t + \Delta t]$ is approximately equal to the probability of failure in $(t, t + \Delta t]$ as :

$$w(t) \approx \frac{\text{Probabilty of failures in } (t, t + \Delta t]}{\Delta t} \quad (5)$$

Alternatively equation (4) could be rewritten as to relate it with equation (1) as:

$$\lambda(t) = \frac{\sum_{i=1}^j n_i(t)}{t} \quad (6)$$

Equation (6) shows the total number of failures occurred on the total time period.

Based on the failure cause, it is also possible to estimate the effect of aging phenomenon by using a shape factor, say α , of the underlying system. The higher the value of α , the higher is the aging effect on the system i.e. $\alpha > 1$. It is important to estimate the value of α to evaluate the impact of aging on the overall system performance and to know when the system might fail. This could be given as:

$$MTTF = \frac{1}{\lambda} \Gamma\left(\frac{1}{\alpha} + 1\right) \quad (7)$$

Where $\Gamma(\cdot)$ is called the gamma function, λ is the failure rate as given in equation (1) and α is the shape parameter to determine the aging effect.

When the aging parameter α is known, then it is relatively easy to calculate the hazard rate, $z(t)$, with Weibull distribution as:

$$z(t) = (\alpha\lambda)(\lambda t)^{t-1} \quad (8)$$

The hazard rate $z(t)$ will increase with time t when $\alpha > 1$.

Step 3 Introduction of correction factor

After analysing the failure causes, it is important to quantify what measures have been adopted for their elimination. One possible way will be to introduce the corrective factor, say γ_i for this purpose. In the table below, a detail of possible situations with respect to possible cause of failure are outlined which might generate after their necessary treatment. The adopted measures are quantified by using the correction factor γ_i for this purpose. There are numerous possibilities to establish the relationship of generic failure causes with specific conditions. These conditions are those which are taken into consideration while dealing with the failure cause. The details of these conditions are listed in Table 1 for approximating the correction factor γ_i .

Table 8 Correction factors, γ_i based on failure cause analysis

γ_i	Explanation/situation
0.1	The failure cause is eliminated, or not relevant
0.5	Measures to prevent the failure cause are implemented
1.0	No specific conditions indicate that anything is changed for the failure cause
1.5	Failure cause not considered
2.0	The situation indicates that the conditions are not favorable for this failure cause
2.5	The situation indicates that the conditions are extra bad for this failure cause
3.0	The conditions of the failure cause have started to propagate
5	The situation is significantly worse with respect to this failure cause and system could go to shutdown at any instant

Step 4 Quantification based on failure causes

The list of details provided in Table 1 is general but it may vary from one failure cause to another one. For example, there are chances to quantify in a different way to estimate the correction factor γ_i for common cause and cascading failures. The reason behind this fact is the impact and nature of such failures on the system's performance. Different signs may appear while diagnosing and treating the CCF during the quantification of β parameters compared to calculating the instances of occurrences (number of failures) for cascading failures.

So keeping in view these issues, we can say that $\lambda_i = \{\lambda_{depend,i}, \lambda_{cascading,i}, \lambda_{independ,i}\}$ which runs from $i=1,2,\dots,n$ failure causes as shown in equation (1). So for a given type of failure based on its cause, the new estimate of failure will be completed as per the format given in Table 2.

Table 9 Failure cause analysis of generic failure causes

λ_i	γ_i	$\lambda_i \times \gamma_i$	Failure cause	Measure implemented, and anticipated effect
$\sum_i \lambda_i \times \gamma_i =$			(adjusted best estimate)	

Step 5 Estimation of failure rates

In the final step, the overall failure rate will be calculated keeping in view the failure causes and their quantification by using the correction factor. So the best estimate λ_{BE} is as under:

$$\lambda_{BE} = \gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \dots + \gamma_n \lambda_n \quad (9)$$

Before making our estimate as conservative, it is better to define it as the mean value plus one standard deviation, say $\square_{CE(Database)}$. The standard deviation of a particular failure is usually provided in database handbooks like it is available in OREDA. So our conservative estimative say, $\square_{CE(Final)}$ may be outlined as:

$$\lambda_{CE(Final)} = \lambda_{CE(Database)} \frac{(\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \dots + \gamma_n \lambda_n)}{\lambda_1 + \lambda_2 + \dots + \lambda_n} \quad (10)$$

$$\lambda_{CE(Final)} = \lambda_{CE(Database)} \frac{\lambda_{BE}}{\lambda_1 + \lambda_2 + \dots + \lambda_n} \quad (11)$$

Results

To understand the impact of failure cause, 50 wind turbines of the same type were selected to analyze the impact of each cause to determine the failure rates. Among those selected wind turbines, failure rates based on failure cause were investigated and the results are shown in the following figure.

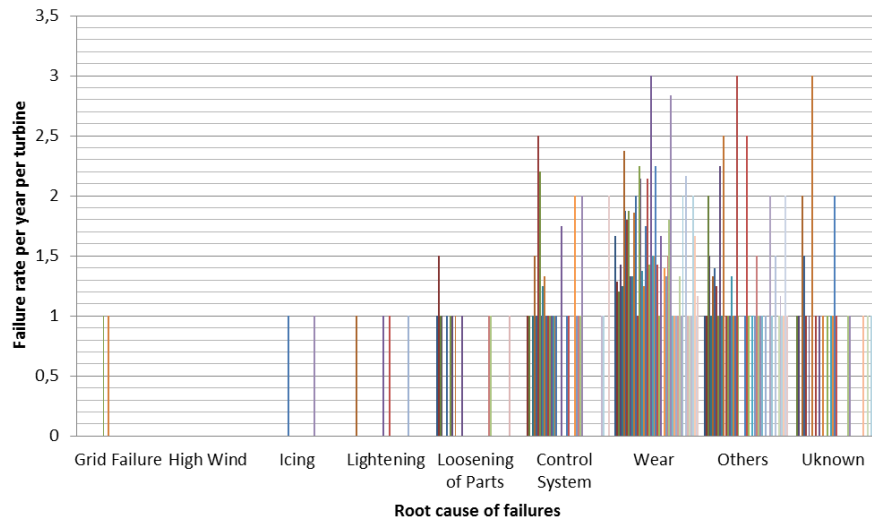


Figure 11: Determination of failure rates based on the failure causes

From Figure 2, it is quite evident that the main causes of failure are related with wear, control, loosening of parts, others and unknown. Only few failures occurred due to lightening, icing and grid failures. The contribution each failure cause was measured vis-à-vis to the given number of wind turbines (50) and the results are outlined in Figure 3. Maximum numbers of wind turbines were affected by the wear, then others and third one are the control related problems.

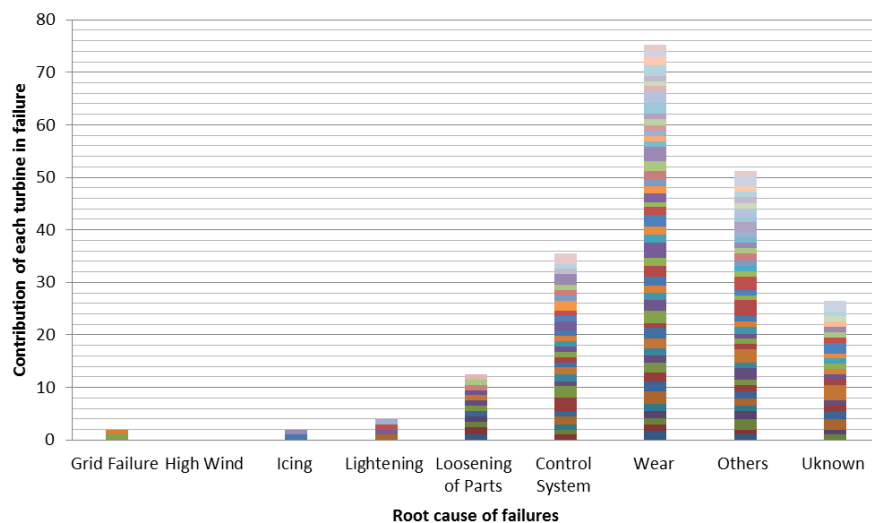


Figure 12: Contribution of failure causes for a given number of wind turbine population

In Figures 2 and 3, a brief overview of failure causes for a given number of wind turbines was presented in order to identify the most important causes of failure. Now the proposed method is to be illustrated here regarding how it works. As per equation (1), n different root causes were responsible for the failure rates. These failure cause n goes from $i=1,2,\dots,n$ which in our case are {Grid Failure, High Wind, Icing, Lightening, Loosening of Parts, Control System, Wear, Others, Unknown}. The overall failure rate will be the sum of these failure causes which could be given in tabular form for some of the wind turbines are shown below:

Table 10: Estimation of initial failure rates based on root causes

Turbine No.	Grid Failure	High Wind	Icing	Lightening	Loosening of Parts	Control System	Wear	Others	Unknown	Total Failures /Year
1	1	0	0	0	0	1	2,25	1	0	5,25
2	0	0	0	0	1	1	2,14	1	1	6,14
3	0	0	0	0	0	1	1,38	1,33	0	3,71
4	1	0	0	0	0	1	1,25	1	1	5,25
5	0	0	1	0	0	1	1,75	1	0	4,75

From Table 3, it means that turbine 1 will experience just more than 5 failures due to different root causes and so on. After determining the initial failure rate, our next job is to analyze the impact of these failure causes on the overall operation of the wind turbine. For this purpose, Fish bone diagrams were prepared for five wind turbines being shown in Table 3. The effect of a possible cause of failure was investigated and two of the highest impacts are shown in Figure 4. From Figure 4(a), it seems that most of the causes were responsible for the wind turbine stoppage. The failure causes of “Others” and “Unknown” were present there to halt the operations. It means that there were instances when it was very difficult to identify any of the established root causes (first seven in Table 3) and were declared as “Others”. Moreover in certain cases, even it was not known the likely cause of failure when the system was shut down and declared as “Unknown”. Figure 4(b) also contains the “Others” and “Unknown” causes and their impact is “Other Consequences”. This is another challenging area to investigate further in detail to find out what happened to the system. The causes of “Wear” and “Control System” are present in Figures 4 (a) and (b) which highlight their importance for taking mitigations measures to eliminate them. In addition to the effects of plant stoppage and other consequences, the impact of “Wear” was resulted into vibration (WT# 1), noise (WT# 3& 5), and cause follow-up damage (WT# 4). It shows that the impact of root causes vary over the time period from one wind turbine to another.

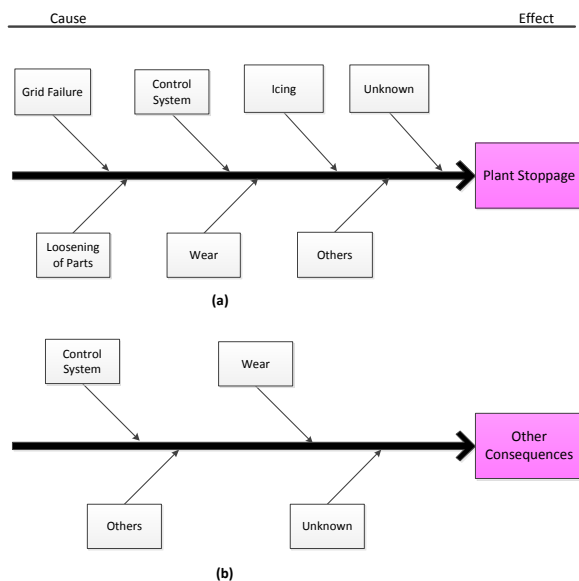


Figure 13: Root cause and effect analysis (a) Plant stoppage (b) Other consequences

After conducting the cause and effect analysis, we might be able say something about the nature of failure like cascading, common cause or independent failure. It seems that the “wear” in turbine 4 had generated “cause follow-up damage” effect which means that it would result in a type of dependent failures (as per Figure1). It is important to further analyze whether it would end in a type of cascading or common cause failure. In the same way, vibration and noise effect might be possible for dependent class of failures. For further analysis, equation (2) could be used to approximate the β factor to estimate the dependency of failures. At this stage, we can fairly say the effect of “Other consequences” might fall in a class of independent failures. Furthermore, as per equation (6), we have calculated the total number of failures which are shown in Table 3.

Aging is another important phenomenon which is directly responsible for a number of failures. Based on the contribution of each failure cause, it is possible to estimate the degree of aging impact on the operations of wind turbines. For this purpose, the relationship of aging parameter (α) has been established with MTTF (Mean time to failure) as per equation (7). In Figure 3, it has been shown that wear is one of the important dominate causes of failures among 50 wind turbines. Now it is necessary to establish the link between degree of wear and aging. We cannot say forthright that there is direct relationship between wear and aging because it depends upon the nature of wind turbine subsystems to investigate this possible relationship. For this purpose, we can dig into detail to find which subsystems of wind turbines were affected of wear. In turbine1, there occurred one failure in rotor blades, converter, mechanical brake, rotor bearings and yaw motor due to wear. There were two and three failures in valves of hydraulic system and yaw system respectively. There were 48 days from one failure to another in valves and there were 145 and 239 days among three different failures in yaw system which is shown in days in the following table.

Table 11: Estimation of aging parameter based on failure rates difference

	Time difference between First to Second Failure (Days)	Time difference between Second to third Failure(Days)
Valves	2	-
Yaw system	6	10

Due to wear, there were only two days from one failure to another for the valves of hydraulic system compared with 6 and 10 days of failure for the yaw system. In Table 4, the data was presented from only wind turbine. Further investigations were carried out to evaluate the time difference between failures for valves and yaw system. It was found out there was less time difference between failures for valves compared with yaw system. This information shows that aging phenomenon is strongly present in valves compared to the yaw system. It also implies to opt for aging replacement models for valves and condition based strategies for yaw system. Based on the estimated aging parameter (α) and failure rates (λ), we can calculate the hazard rate as per equation (7).

Based on the failure cause analysis, our next task is to estimate the correction factor (γ_i) as per the format of Table 1. From Figure 3 and Table 3, it is quite evident that wear is the most important failure cause and demands improvement in the future turbines to reduce its impact on the system's performance. For demonstration purposes, it will be shown how the failure rates for new turbines in offshore environment is to be calculated based on Table 1 and 2. Turbine no. 2 from Table 3 is selected for this purpose to estimate the reliability of the same type of wind turbine in offshore locations. The said wind turbine is located across the shore and it is relatively easy to estimate how failure rates will change from shore to offshore location. For choosing a suitable value of correction factor γ_i from Table 1 based on root cause i , it is important to evaluate how that particular cause is affecting the existing installations and what are expected challenges at the new environment. It is nearly impossible to eliminate all the failure causes from new machines.

For wear, the value of γ_i could range from 0.5 to 2 based on Table 1. The rationale for not taking value of 0.1 is obvious that it will also be present in the new machines. In the new machines, work is underway to reduce the number of components (e.g. drive trains without gearbox) which means that measures are adopted to reduce the impact of wear. But still at the same time, it is expected that wear rate might be relatively high in offshore locations due to marine environment compared to land based installations. So the situation indicates to opt for the value of γ_i between 0.5 to <1.5 which might be assumed as 1.25 at this moment. In the same way, the values of γ_i for other root causes have been worked out and summarized in Table 5. The values of λ_i are assumed in Table 5 keeping in view the measures being adopted to enhance the reliability of offshore wind turbines.

Table 12: Estimation of failure rate based on root causes

λ_i	γ_i	$\lambda_i \times \gamma_i$	Failure cause	Measure implemented, and anticipated effect
2,75	1,25	3,44	Wear	Less components, Robust design
0,1	0,5	0,05	Control System	Robust control system
0,5	0,5	0,25	Loosening of Parts	Higher structural integrity
0,005	0,5	0,00	Lightening	Novel coatings and protections
0,05	0,5	0,03	Grid Failure	Improved grid connectivity
0,75	2,5	1,88	High Wind	Efficient brake system
0,5	2	1,00	Others	Efficient fault detection and condition monitoring system
0,1	2,5	0,25	Unknown	
$\sum_i \lambda_i \times \gamma_i =$		6,89		

In Table 5, the values of γ_i for control system, loosening of parts, lightening and grid failures are assumes at 0.5 keeping in view the fact these causes might be addressed in a good way for new machines. The high wind root cause is very serious in case of offshore wind turbines because wind is abundantly available in sea compared with land. So this root cause has been given higher values. The root cause others is serious because it is not really possible

to find what happened to the system. Even the unknown is more serious compared with others and the higher frequency of this cause might prove detrimental in terms of reducing the operational costs. For this reason, the failure causes of others and unknown, should be addressed by developing efficient fault detection and condition monitoring systems.

As per equation (8), the value of λ_{BE} has been estimated in Table 5 for turbine no. 2 and the same for $\lambda_{CE(Database)}$ has been done in Table 3. So the final value of failure rate as per equation (10) will be calculated as under:

$$\lambda_{CE(Final)} = 6,14 \frac{6,89}{4,76} = 8,90$$

So the new expected total failure rate per year of turbine no. 2 are 8,90 which is an initial estimate keeping in view the offshore environment and the failure rates of land based wind turbines. Wear is the important dominant cause for failures and it is expected that it will cause more failures in marine environment. So that is the reason that it is being given more weightage in Table 5 and it is almost half of the total failure rate for new wind turbines at offshore locations. If the measures will be adopted to reduce the wear or it is handled efficiently, then it is expected that failure rate $\lambda_{CE(Final)}$ might reduce significantly.

Summary & Conclusion

In this paper, a methodology to estimate the reliability parameters based on the initial data is proposed. It has been described how to calculate the necessary parameters which are important for maintenance optimization of offshore wind turbines. In the proposed procedure, it has been outlined how to approximate the reliability of new machines based on the existing one. While translating this experience from onshore to offshore wind turbines, different challenges and issues have been highlighted which needs our further attention to address them in more detail.

While working with root cause analysis, it was obvious that wear is the most dominant cause of failure which demands to have new materials with less wear. It is also clear that suitable measures are necessary to reduce the frequency of failure causes like others and unknown. If the frequency of such failure causes would not be reduced, then it might prove a hindrance in achieving the higher reliability and availability levels for offshore wind turbines compared with their competitors on land based installations.

Further refinement and more detail are required to improve the quality of proposed method which is still underway.

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Accessing offshore wind turbines for maintenance – calculating access probabilities, expected delays and the associated costs using a probabilistic approach

Julian Feuchtwang, David Infield
University of Strathclyde, Glasgow, UK
julian.feuchtwang@eee.strath.ac.uk

Abstract

There are ambitious plans in place for the expansion of offshore wind-power capacity in the EU and elsewhere. However, the cost of energy from offshore wind is much higher than that from land-based generation and anything between 15% and 30% of this cost is attributable to the cost of operation and maintenance (O&M). For exposed UK round three sites these costs could be higher still. The stochastic nature of the occurrence of faults, down-times due to adverse weather and sea-state and the associated losses in energy production, as well as vessel and personnel costs, all add to the potential risk to the finance of an offshore wind farm project. There is a clear need to estimate these effects and the risks associated with them when planning and financing a wind-farm. Key to all such calculations are the restrictions on safe access for maintenance associated with vessels and access methods and the consequent delays caused by adverse sea-state and weather. A computational approach has been developed at University of Strathclyde, based on an event tree and closed-form probabilistic calculations, enabling very fast estimates to be made of offshore access probabilities and expected delays using a simple spreadsheet. Examples are presented for calculations of accessibility. Turbine availability and loss of energy production are calculated based on given turbine component reliability data together with an agreed maintenance scheme. Direct maintenance cost and revenue lost due to down-time can also be calculated with suitable data on the costs of personnel, components, and vessel hire as well as electricity unit and ROC prices, and examples are given. Sensitivities to some of the key parameters are also presented.

Keywords – Offshore Wind, Operation and Maintenance, Risk, Accessibility, Availability, Sea-state, Probabilistic Analysis

Introduction

Operation and maintenance can strongly affect the financial and technical risk of offshore wind energy, largely through uncertainties in the repair process and particularly constraints on access to the turbines. Access for maintenance, particularly in adverse sea-states, can be challenging and will have a major impact on turbine availability. There is a pressing need for improved understanding of this effect. A probabilistic event-tree model has been developed as an alternative to conventional Monte Carlo methods that require repeated extensive simulations. Expected values of delays due to sea-state can be expressed as closed form expressions depending on the probability distributions of sea-state ‘storm’ and ‘calm’ duration.

Using records of significant wave height, sea-state duration distributions for a given threshold wave height can be computed directly from level-crossings and 'storm' and 'calm' durations. Weibull distributions are generally a good fit for these distributions and relevant parameters can be calculated using maximum likelihood methods. The contribution from each branch of the event-tree to the expected delay time is a function of a small set of parameters calculated from the duration probability distributions. If these distributions are used in Weibull form, they can be calculated directly from the calm and storm duration Weibull parameters for the particular wave-height.

Using subsystem reliability and repair time data, a simple spreadsheet can then be used to estimate annual expected delays due to each subsystem as well as the sensitivities of delays to site, turbine and access parameters. In this work, subsystem reliabilities and repair times are based on operational data from Danish and German turbines based on land. Assumptions are also made about access methods for repairing different subsystems and consequently permissible sea conditions.

Calculations for wind turbines located at North Sea sites for which wave data are available indicate that annual down-times are dominated by repairs to the blades, generator and gearbox. These are not necessarily the subsystems with the highest failure rates but those requiring long repair windows and whose repairs currently require large crane vessels, the use of which is severely restricted by sea-state. The greatest influence on down-time and availability is found to come from changes in the access conditions for repairs, by reducing reliance on 'sensitive' vessels, by reducing repair time at the turbine and by reducing vessels' sensitivity to sea-state.

The advantage of the approach developed is that it is possible to explore the impact of changing access thresholds, reliabilities or site parameters quickly and easily without having to run a long series of simulations for each new situation.

Using suitable data on the costs of personnel, components, and vessel hire as well as electricity unit and ROC prices, the cost implications of maintenance and lost revenue (due to down-time) can also be calculated using the probabilistic methodology outlined above.

Methodology for estimating access delays

The aim of the work undertaken was to arrive at estimates of non-availability of wind turbines recently and/or currently being installed offshore, overall and broken down by sub-system. The approach adopted is that of a probability 'event tree' to facilitate rapid assessment of a wide range of input data and scenarios. The paper is concerned with unplanned repairs and the problem of whether access is possible immediately or only after a delay. No attempt has been made to model regular, planned maintenance. Access conditions have been somewhat simplified: for any given fault, it has been assumed that the necessary repair requires the use of a certain vessel type that has known access limits that can be expressed in their simplest terms as a threshold wave height, H_{th} . It has further been assumed that the repair takes a certain time to complete, and that the wave height restriction applies throughout that time period. The availability of suitable vessels, spares, and personnel are assumed ideal in the analysis presented here, but this could be generalized in future work.

A. Requirements for model

There are several possible approaches to modelling offshore access and its effect on operation and maintenance and thereby on turbine availability. Any such approach will always require certain key elements: wind and wave data; failure rate data for each relevant

component or sub-system and each type of failure; actions required in response to each type of failure, particularly materials, personnel, tools and plant and time needed and by implication the vessels to be used; limiting operational conditions, expressed as threshold wind speeds and wave heights for safe operation (characteristic of the vessel required and the transfer systems); travel and operating times required.

How these elements fit together is shown schematically in Figure 14.

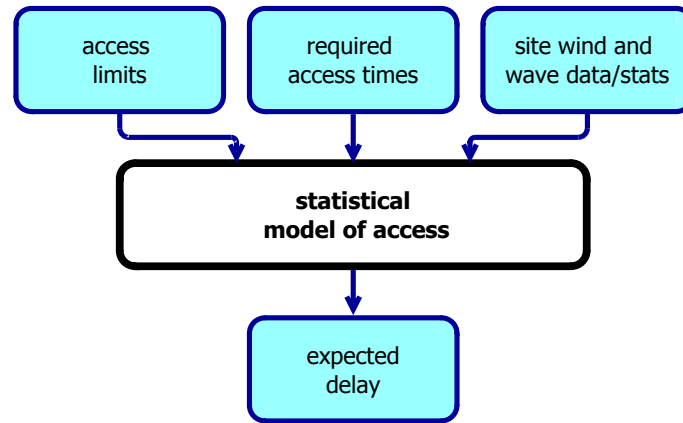


Figure 14: Schematic diagram of offshore access delay calculation

Monte Carlo methods are most commonly used for estimating offshore delays and system down-time. Their main disadvantage is that many runs are required for convergence. A more direct approach to modelling delays is to construct an 'event tree'. This describes every conceivable event and its alternatives, prerequisite conditions and consequences, with probabilities assigned to each 'branch'. The advantages are transparency and speed and simplicity of computation and these make it straightforward to explore trends by varying input parameters.

B. Probabilistic delay model

The probabilistic model of operational delay developed here is based on a number of simplifying assumptions that, for the sake of clarity, allow the presentation of a very simple event tree and the derivation of relatively simple expressions for expected delay. For any given offshore operation, the starting point is to define the wave statistics of the given site, the operational limits, which may be expressed as a limiting or threshold wave height for the given vessel, as well as the operation time required (consisting of travel time plus repair time). The expected or mean delay time can then be calculated and thereby down-time.

A number of assumptions are made: faults occur randomly and independently; offshore, repairs are completed in a single visit, which may however last several days; a single operational limit applies to each operation (significant wave height); short term forecasts of sea state are available corresponding to the length of the required operation.

A simplified event tree is shown in Figure 15 below; this accounts both for the threshold wave height and the required time window.

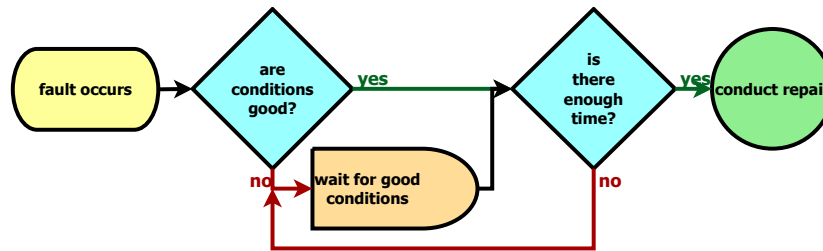


Figure 15: Simplified event tree for offshore repairs

It is possible to identify 4 distinct situations when a fault occurs (see Figure 16):

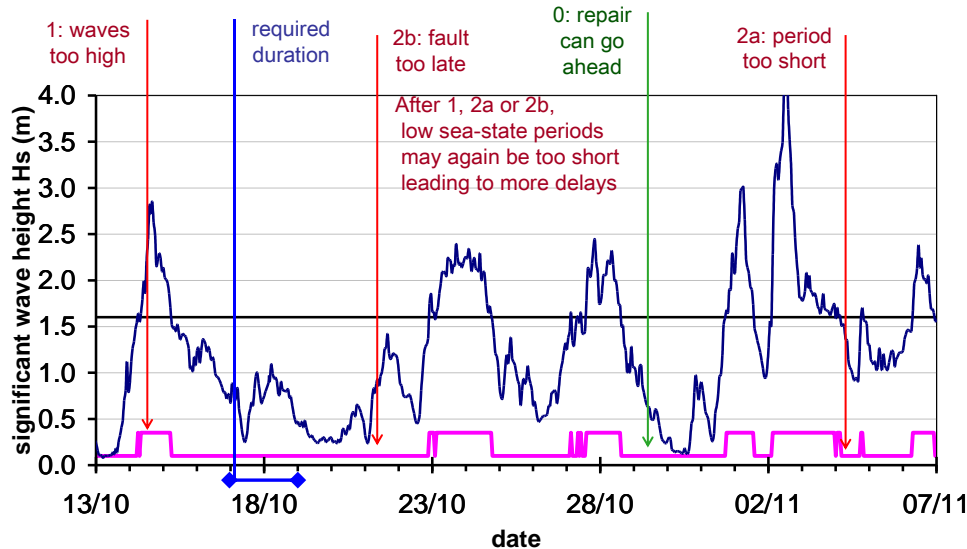


Figure 16: Example wave-height time-series with illustration of types of delay

0: the sea state is low enough and there is sufficient time left to carry out the operation (no delay)

1: the sea state is too high to gain access. The next period of low sea must be waited for. (1st order delay)

2a: the sea state is low enough but is predicted to be too short to effect repair. This period and the subsequent period of high sea-state must be waited through. (2nd order delay, type a)

2b: the sea state is low enough and the predicted period is long enough but there is insufficient time left in the current period to complete the operation, i.e. the fault occurred too late in the weather window. As above, this period and the subsequent period of high sea-state must be waited through. (2nd order delay, type b)

A period of high waves preventing access will eventually be followed by a period of suitably low wave height to allow access, but this may not be long enough to effect the repair and would then lead to a further cycle of delay. Similarly, after a 2nd order delay, there will be a period of high waves followed by a period of low waves and, again, this may not be long enough.

The event tree can also be expressed in a more detailed form as shown in Figure 17 below.

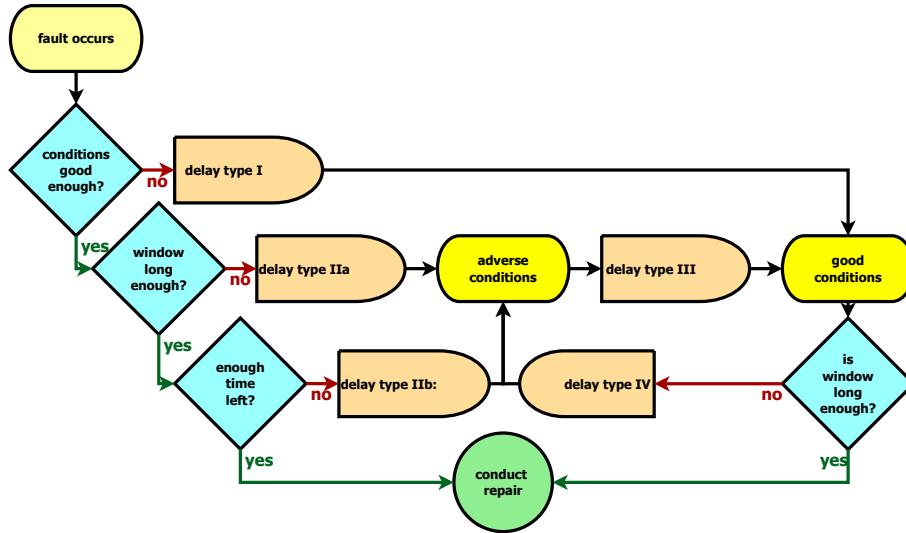


Figure 17: Full event tree for offshore repairs

The probabilities of occurrence of periods of different duration as expressed in the probability distribution are based on numbers of occurrences expected in, say, a year or alternatively a season. In contrast a fault is more likely to occur in a long period than a short one so whether an initial fault occurs in period of type 0, 1, 2a, or 2b, must be time biased. Thus, the expectation of delay resulting from the fault is determined by the ‘time-biased’ ‘storm’ (exceedence) and ‘calm’ (non-exceedence) duration probability distributions. On the other hand, the probability of a subsequent period being long or short is not biased in this way and, assuming independence, follows the original unbiased occurrence probability distribution.

The derivation of the relevant expressions for the probabilities of each of the above and the respective expected values of delays is omitted here but summary equations are presented below.

$P_0(H_{th}, t_{req})$ gives the probability that the wave height will be below a given threshold, H_{th} , and remain so for a clear window of time, t_{req} :

$$P_0(H_{th}, t_{req}) = [1 - P_H(H_{th})] \cdot [1 - M_{qn}(H_{th}, t_{req}) - Q_n(H_{th}, t_{req}) \cdot t_{req} / \tau_n(H_{th})] \quad (1)$$

where $P_H(H_{th})$ is the probability that wave height exceeds the threshold H_{th}

$q_x(H_{th}, t)$ and $q_n(H_{th}, t)$ are the storm and calm duration probability density functions for a threshold wave height of H_{th}

$Q_n(H_{th}, t)$ is the probability that a calm with $H_S < H_{th}$ has a duration longer than t_{req} , and is found by integrating $q_n(H_{th}, t)$ up to t_{req}

$M_{qn}(H_{th}, t_{req})$ is the normalised partial 1st moment of $q_n(H_{th}, t)$ up to t_{req}

$\tau_n(H_{th})$ is the mean calm duration

$\tau_x(H_{th})$ is the mean storm duration

$M_{qnx}(H_{th})$ is $\frac{1}{2}$ the normalised complete 2nd moment of $q_x(H_{th}, t)$

and $M_{qqn}(H_{th}, t_{req})$ is $\frac{1}{2}$ the normalised partial 2nd moment of $q_n(H_{th}, t)$ up to t_{req} .

The expected value of delay, taking into account all contributions, and with arguments omitted for clarity, is given by:

$$\begin{aligned}
 E[t_{\text{delay.total}}(H_{th}, t_{req})] = & P(H_{th}) \cdot M_{\text{qpx}}(H_{th}) \cdot \tau_x(H_{th}) \\
 & + \frac{(1 - P(H_{th}))^2}{P(H_{th})} \cdot M_{\text{qqn}}(H_{th}, t_{req}) \cdot \tau_x(H_{th}) \\
 & + P(H_{th}) \cdot Q_n(H_{th}, t_{req}) \cdot \frac{t_{req}^2}{2\tau_x(H_{th})} \\
 & + P(H_{th}) \cdot Q_n(H_{th}, t_{req}) \cdot t_{req} \\
 & + (1 - P(H_{th})) \cdot M_{\text{qn}}(H_{th}, t_{req}) \cdot \tau_x(H_{th}) \\
 & + [P(H_{th}) + (1 - P(H_{th})) \cdot M_{\text{qn}}(H_{th}, t_{req})] \cdot t_{req} \\
 & + \frac{[P(H_{th}) + (1 - P(H_{th})) \cdot M_{\text{qn}}(H_{th}, t_{req})]^2}{P(H_{th}) \cdot Q_n(H_{th}, t_{req})} \cdot \tau_x(H_{th})
 \end{aligned} \tag{2}$$

C. Sea-State Representation

There are many different sources and types of data that can be used to characterize a local sea-state. For this work it has been assumed that adequate time-series data exist for significant wave height, H_s . These data are used to fit Weibull probability distributions for H_s and for durations of calms and storms corresponding to the threshold wave height under consideration. A combination of the method of moments and maximum-likelihood analysis was used.

An example is shown in Figure 18 and Figure 19 using data from the Barrow OWF site (at 054° 0.0'N 003°18.8'W) from August 1992 to November 1993, and was downloaded from the web-page of the British Oceanographic Data Centre (BODC) [1].

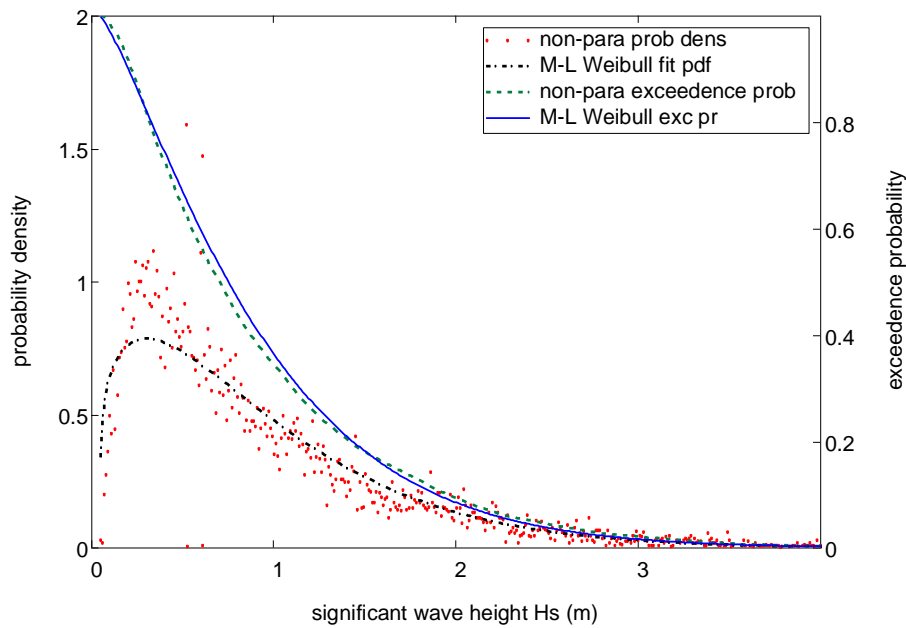


Figure 18: Significant wave height distributions for Barrow OWF

From these distributions, the required moments can be calculated, and from these the expected delay can be estimated as set out above in eqn. (2).

The outcome of the probability tree calculation is a set of curves giving delay time as a function of limiting sea-state (threshold wave height) and operational time required. An example family of curves in Figure 20 is based on the same Barrow OWF site data as in the figures **Error! Reference source not found.**. They show delay time against operation time for a range of threshold wave heights. It can be seen that the delay time is very sensitive to both operation time and threshold. It should also be noted that they are highly sensitive to the specific site's sea conditions.

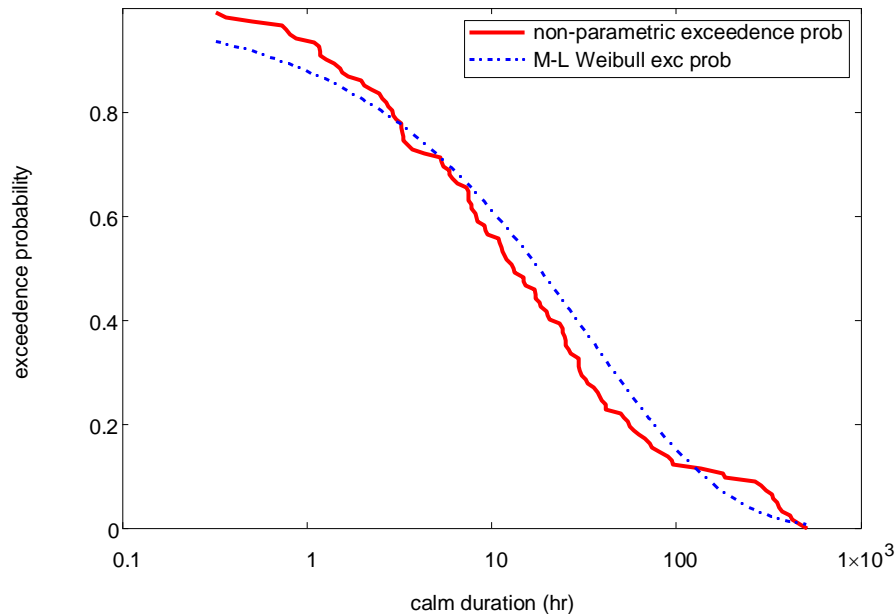


Figure 19: Calm duration exceedance distribution for Barrow OWF

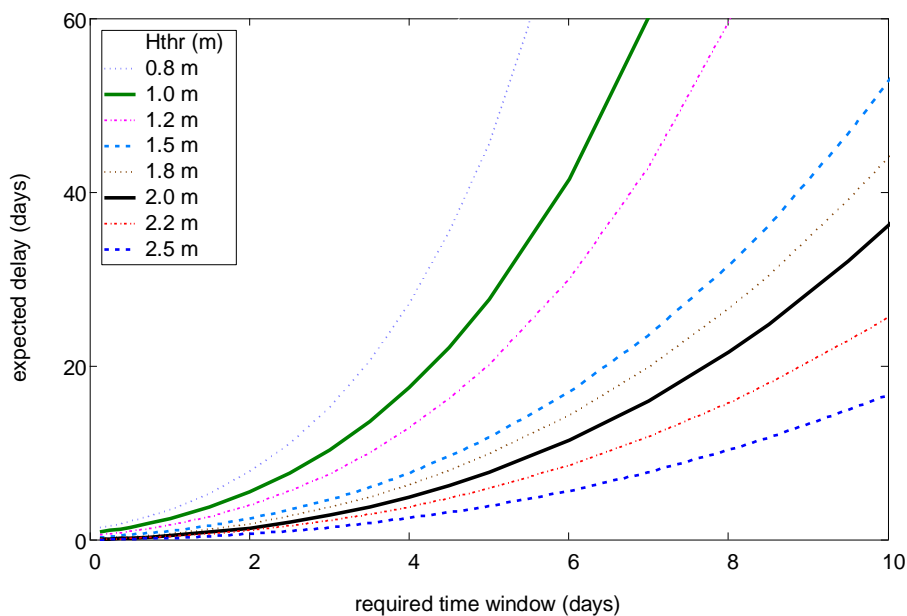


Figure 20: Expected delay time vs. repair time, for different wave height thresholds at Barrow OWF site

Example application of model: assessing influences on turbine availability and costs

A. Reliability and maintenance data sources

In order to estimate the impact of maintenance access on revenue, it is necessary to estimate total down-time. Ideally, data are needed for each fault type on failure rate, operation type and time required, 'muster time', vessel required and its operational limits and speed.

There are virtually no detailed data in the public domain regarding offshore wind farms so data from land-based wind farms have been used. Numerous sources of data are available, each with strengths and weaknesses. For our purposes, we have derived a baseline description of component reliability and repair times synthesized from a number of published reports and shown here in Figure 21.

For this study, an overall whole-turbine failure rate has been derived from [2], where a trend can be observed of failure rate increasing with turbine size. A baseline turbine with 3.2 MW rating was chosen and an appropriate figure of 3.5 failures per year was assumed. The subdivision of that failure rate between subsystems was derived from [3] (where only percentages are given). Proportions of failures were allocated to different severities of repair category, where the categories themselves and the parameters associated with them are largely derived from [4]. The relative proportions allocated were checked against [5], where a loose division is made between major and minor repairs, i.e. longer or shorter than 24 hours respectively. The process of creating the baseline dataset is discussed in greater detail in [6] (though some figures used in this paper are more recent). There is also an explanation of sources of cost data and of how cost calculations are carried out [ibid].

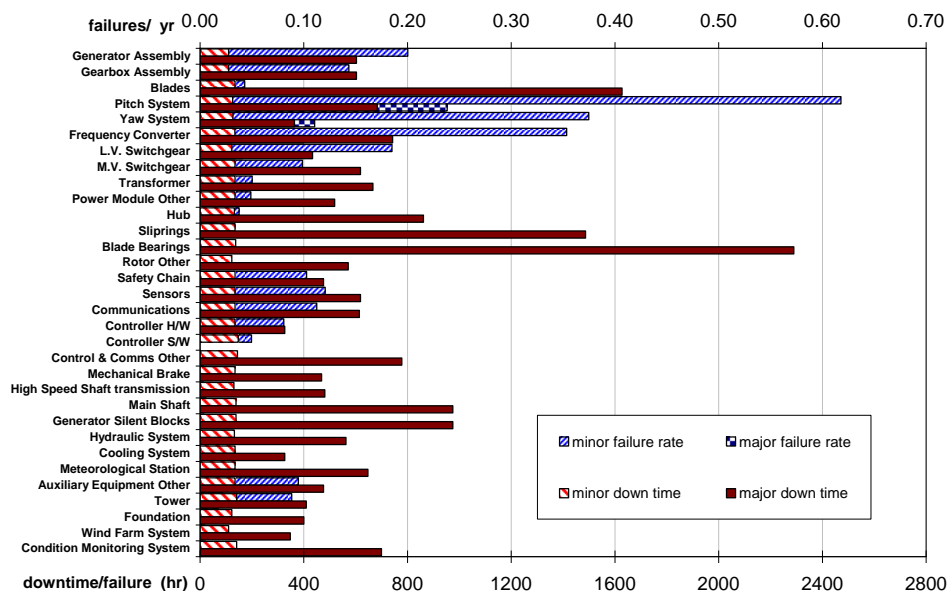


Figure 21: Baseline case subsystem failure rates & down-times per failure

All calculations were performed in a spreadsheet. (A small macro is required to calculate the incomplete gamma function, though there are routines and numerical recipes in the public domain). For any one fault class calculation, an appropriate threshold is set, the total offshore operation time is estimated from a lead time, a travel time, positioning time and a

repair time and the corresponding expected delay time is calculated. The expected annual delay caused by that fault class is the product of failure rate per year with the delay time per fault. The sum of all the subsystems' annual contributions to down-time gives the total expected annual down-time and thereby the (un)availability.

Figure 22 clearly shows that both maintenance and loss of revenue have major impacts on costs and that the former is dominated by vessel costs.

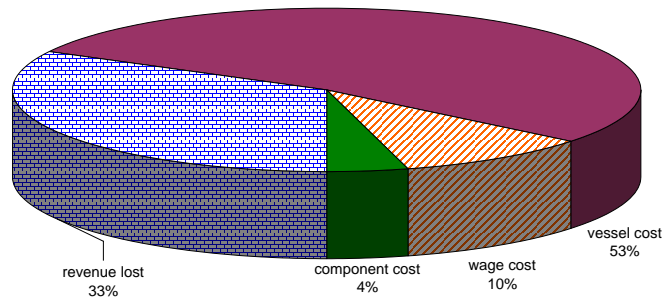


Figure 22: Baseline contributions to cost

Sensitivities to key operational parameters

The base line case gives an expected annual loss of approx. 876 hours or 36.5 days, equivalent to an availability of about 90%. As can be seen in Figure 23, the annual down-time is in the main dominated by the large subsystems, generator, gearbox, and power electronic converter, as well as the pitch mechanisms. This is true to a greater extent than might be guessed just from failure rates and repair times. Of course, these figures must be treated with caution but they illustrate the extent to which delays to repairs on large subsystems are exacerbated by the long operational time needed and the requirement for vessels that are sensitive to sea conditions.

The effect of changing repair times, failure rates, and access thresholds (for large and small vessels separately) was modelled by scaling the baseline case figures by $\pm 30\%$. In addition, sensitivity to sea-state conditions is presented. Curves of sensitivity to lead times and vessel speeds have been omitted for clarity as the sensitivities are so low.

It can be seen in Figure 24 that, of the factors that can be influenced at a particular site, the thresholds for minor and major vessels have by far the greatest effect on availability, with the former having slightly more effect. The effect of site conditions is also very strong, but it can not always be influenced – the choice of sites may be limited. Repair time and failure rate have significant but somewhat smaller effects. In the figure, failure rate appears to have a greater effect than repair time but in reality this is not the case as a percentage change in failure rate in this model applies across all repair categories, minor and major.

If lost revenue is examined rather than availability, as in Figure 25, vessel thresholds and site conditions still have the greatest effect, but the differences between major and minor failures seem to be reduced. It should be noted that when energy generated and revenue lost are calculated, a distinction is made between stoppages in high and low wind conditions. Finally, operation and maintenance cost is shown in Figure 26. Here it can be seen that there is a large difference in the overall cost of major and minor repairs, largely due to the day-rate of heavy lift vessels.

Note that these results are somewhat different from those presented previously [7]; this is believed to reflect refinement in the representation of repair times.

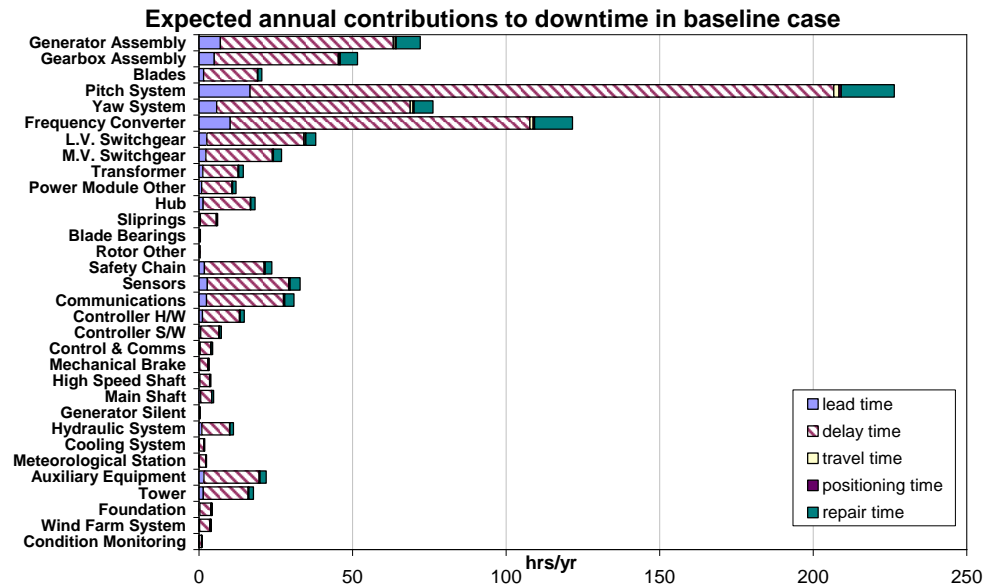


Figure 23: Expected annual contributions to downtime by subsystem

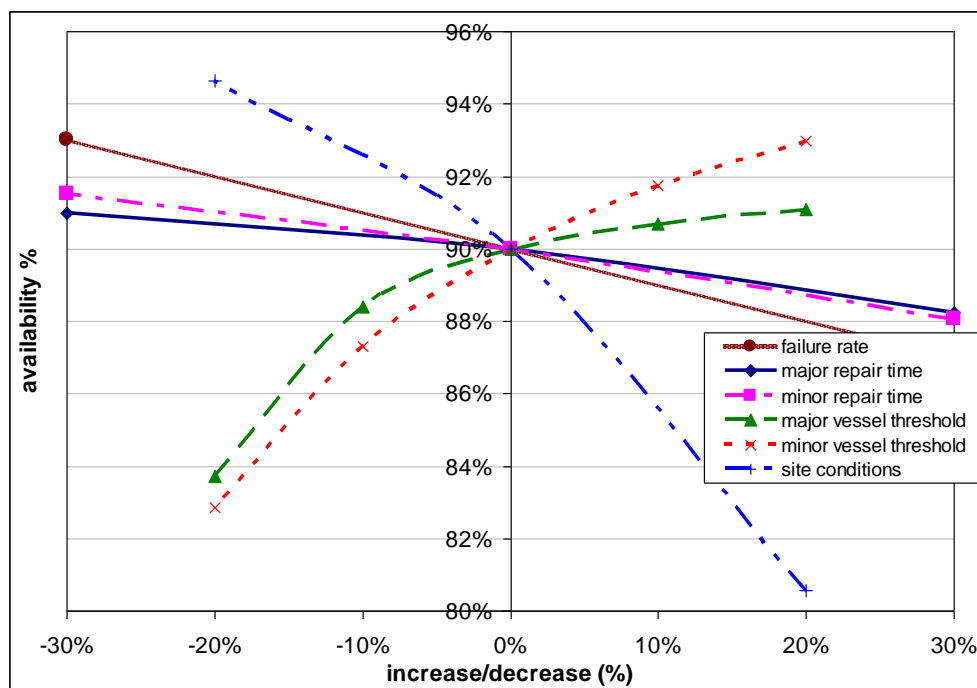


Figure 24: Sensitivity of turbine availability to different factors

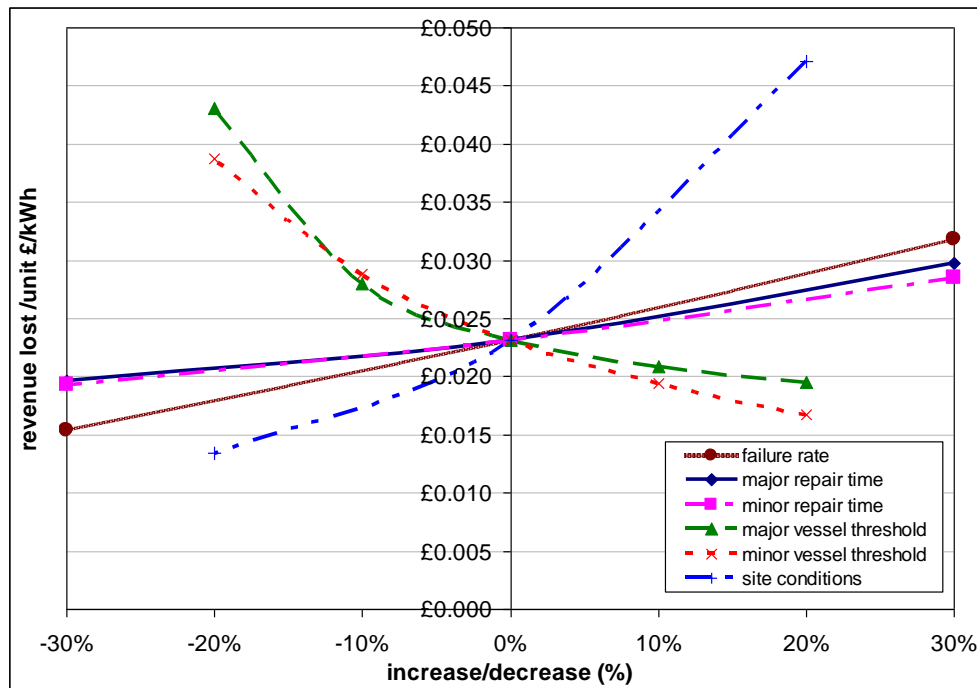


Figure 25: Sensitivity of lost revenue to different factors

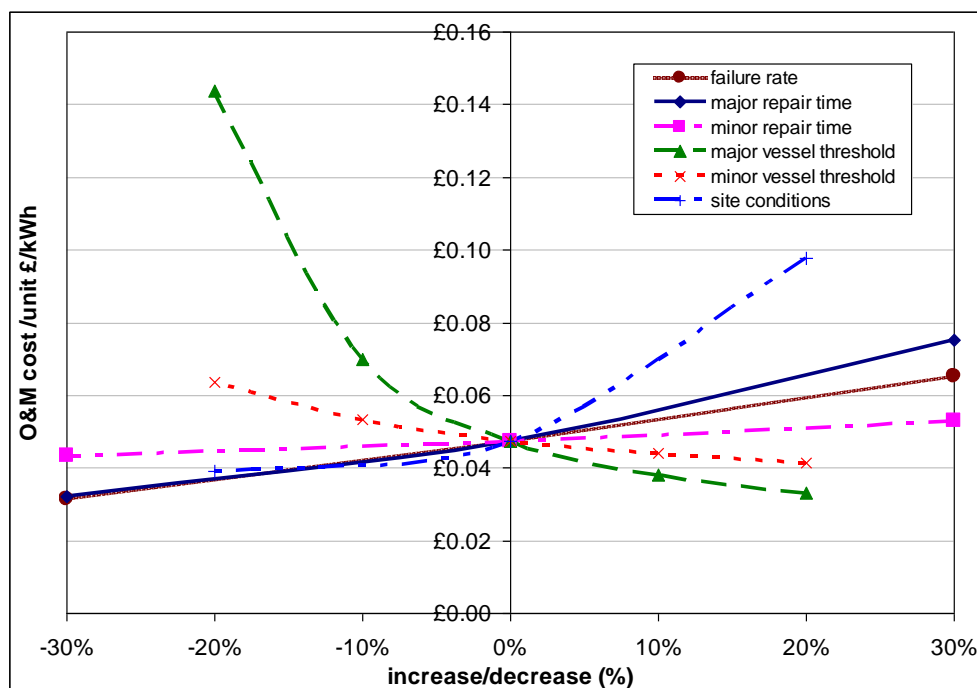


Figure 26: Sensitivity of O&M cost per unit to different factors

Summary & Conclusion

A method has been presented for calculating the expected delays to offshore operations directly from probabilities assigned to the branches of an event tree.

The current lack of data in the public domain regarding offshore wind farms makes validation of the methodology difficult.

The advantage of the approach developed is that it does allow rapid investigation of the influence of various factors on downtime without having to run a long series of simulations for each new situation.

Calculations indicate that annual down-times tend to be dominated by repairs to the generator, gearbox, converter, and pitch mechanism. Not all the critical subsystems have the highest failure rates but they tend to require long repair windows and require large crane vessels, the use of which is severely restricted by sea-state. The greatest influence on down-time and availability is found to come from changes in the access conditions for repairs, by reducing reliance on 'sensitive' vessels, by reducing repair time at the turbine and by reducing vessels' sensitivity to sea-state.

The cost of failures is dominated by day-rates for heavy lift vessels required for major repairs and replacements. The greatest impact on costs would be achieved by reducing the frequency of these types of failures and reducing the repair time needed, as well as by enabling repairs to be carried out in a wider range of conditions.

Future work will concentrate on validation and should include the calculation of confidence limits on the results presented here, these being expected values.

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Risk related to Large Scale Implementation of Wind Power into a Regional Power Transmission System

Christopher J. Greiner¹, Johan Solvik¹, Yongtao Yang¹,
Tore Langeland¹

¹Det Norske Veritas, Norway
Christopher.Greiner@dnv.com

Abstract

This paper presents a methodology to quantify wind power's contribution to power system adequacy in addition to violations of operating reserve requirement. The methodology is based on discrete event simulations combined with optimal power flow simulations, using a novel power system simulation and analysis tool developed at DNV. A case study is performed using the IEEE-Reliability Test System as the model of the power grid, with wind power generation data from Denmark. Results show that wind power's relative contribution to system adequacy drops as wind power penetration increases, which is in line with reported studies of real systems. In addition, the violations of reserve margins tend to increase with increasing wind penetration.

Keywords – Discrete event simulation, Generation Adequacy, Monte Carlo Methods, Optimal power flow, Reserve planning, Risk Assessment, Wind power integration, Wind forecast uncertainty

Abbreviations

AC: Alternating Current
EIR: Energy Index of Reliability
IEEE-RTS: The IEEE Reliability Test System
HVDC: High Voltage Direct Current
MTTF: Mean Time to Failure
MTTR: Mean Time to Repair
MVA: Mega Volt Ampere
OPF: Optimal Power Flow
PCC: Point of Common Connection
SD: Standard Deviation
TSO: Transmission System Operator
VOLL: Value of Lost Load

Introduction

By 2020, Europe could have a total of 230 GW of installed wind power capacity, which would produce 581 TWh of electricity, or 15.7% of total electricity consumption [8]. Wind

installations will tend to concentrate around areas with good wind resources, and for this reason the North Sea region (both on- and offshore) will see a significant increase in wind power capacity in the coming decade. Some Transmission System Operators (TSO's) in Europe already have significant wind penetration levels, reaching up to and above 60% of the peak system load [9]. Due to its variability and prediction uncertainty, wind power cannot replace conventional power plants on a 1:1 basis.

System studies addressing the contribution of wind power to system adequacy and the need for additional operating reserves will be essential for risk management in power systems with high wind energy penetrations. This paper presents a method to conduct such studies, using a novel power system simulation and analysis tool, which combines discrete event simulations with optimal power flow simulations. A case study was set up based on the IEEE-Reliability Test System [10], with four cases of installed wind power (10, 20, 30 and 42% of annual energy penetration) using wind power generation data from Denmark. The study quantifies wind power's relative contribution to system adequacy by assessing the type and capacity of conventional generators that can be decommissioned while maintaining the level of load shedding. In addition, operating reserve requirements and reserve violations are quantified.

Currently only a handful of tools exist for probabilistic adequacy evaluations of power systems. In general the tools have many gaps that limit wide spread implementation [11]. In addition there is no known commercial tool for probabilistic security assessments.

Methodology

The study is conducted using a novel power system simulation and analysis tool – *PowerRisk*. *PowerRisk* can be used for probabilistic adequacy evaluations of AC (Alternating Current) power systems including also radial HVDC (High Voltage Direct Current) lines. *PowerRisk* is developed by combining existing software in a new way and adding additional functionality. Figure 27 shows a simple flowchart of how *PowerRisk* works:

- Reliability block models have been developed in the commercial software *ExtendSim*¹. *ExtendSim* reads reliability and maintainability data of the system components (such as overhead lines, transformers and generators. Time-series of load and variable power sources such as wind power are also read, in addition to a generator maintenance schedule. *ExtendSim* can deal with interdependencies such as common cause failures and circuit breaker malfunctions, in addition to multiple distributions for time to failure and time to repair.
- *ExtendSim* generates discrete events of the power system state. *ExtendSim* sends system state arrays to Matlab and invokes *Matpower* [12], a free Matlab Power System Simulation Package that holds the full electrical model of the power system.
- *Matpower* runs an AC optimal power flow (OPF) with the updated system state. An OPF represents the power system by a one line diagram and per unit (p.u.) system and uses linear programming to find the lowest cost solution to the steady state

¹ <http://www.extendsim.com/>

power flow problem. In Matpower, load shedding is enabled by defining part of or the entire load as dispatchable, with a dispatch cost equal to the Value of Lost Load (VOLL). The OPF formulation in Matpower has been extended by including transformer tap changers and shunt reactors as continuous variables as opposed to fixed parameters.

- ExtendSim reads the results from Matlab and moves on to the next event. The process continues until the end of the simulation period.

The total simulation time depends on the number of events and the time it takes to perform each OPF simulation. The user can specify which results are to be read and analyzed by ExtendSim. For the study presented in this paper, the results of interest are:

- The frequency, duration and level of load shedding
- The frequency and duration of reserve violations

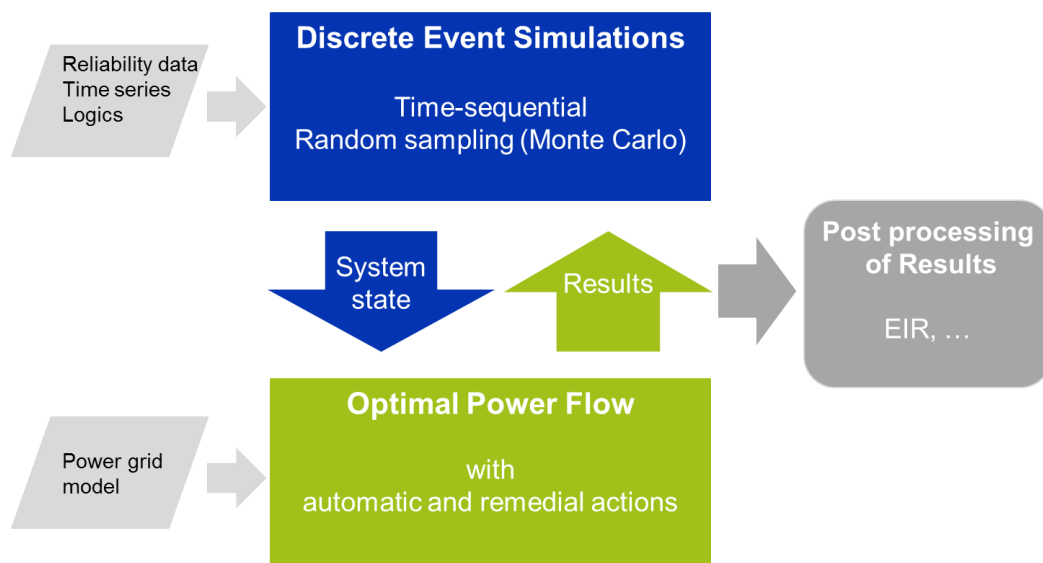


Figure 27: High level schematic of the PowerRisk tool.

Case Study

A. Power System Model

The IEEE one-area Reliability Test System (RTS) [10], from now on referred to as IEEE-RTS, is used as the model of the power system. The IEEE-RTS is a hypothetical system meant to provide a benchmark for which to test and compare various methods of reliability analysis of power systems. Ref. [10] specifies electrical data and reliability/maintainability data for all buses, branches and generators. Wind power plants were added to the IEEE-RTS, and the modified system is shown in Figure 28. Two new lines were added between buses 17 and 15 and 11 and 15 to increase the power transfer capability due to high concentration of wind power in this area.

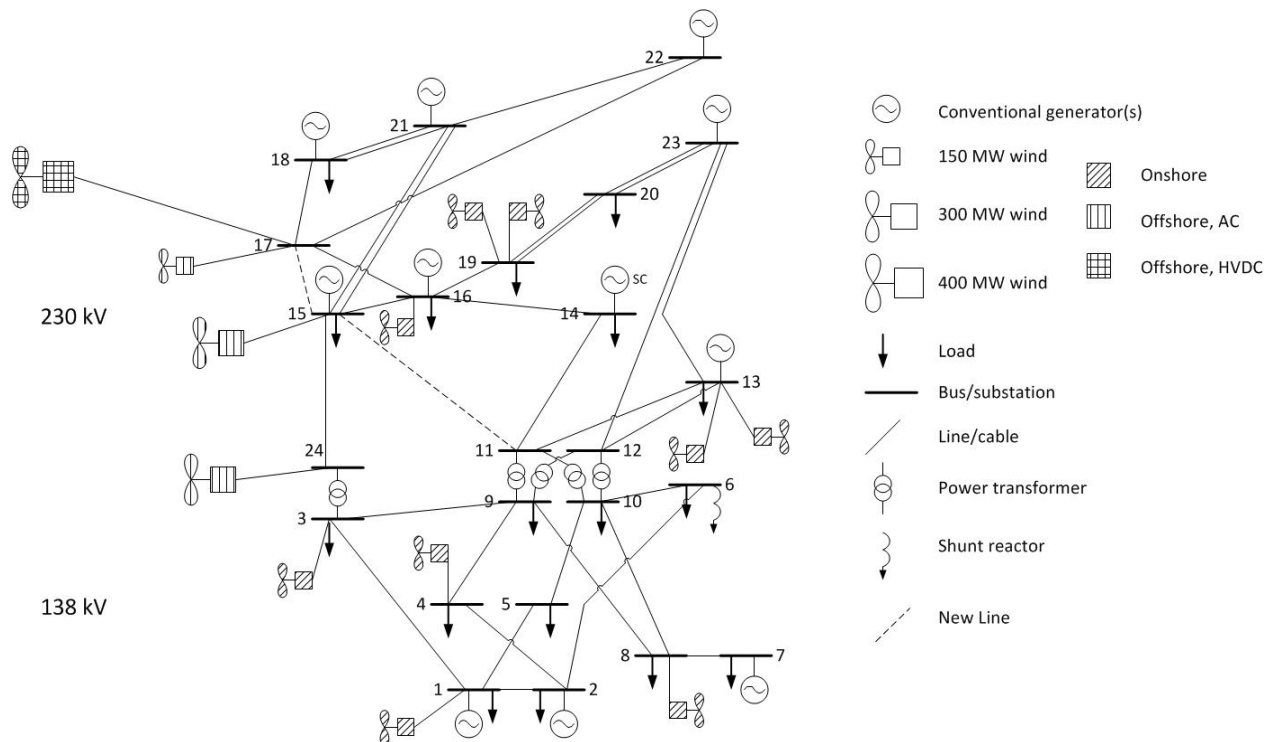


Figure 28: One line diagram of the IEEE-RTS [10], included wind power plants and new lines.

Power Grid

Table 13 states the power flow capacity in MVA (Mega Volt Ampere) of the branches in IEEE-RTS included the two new lines.

Table 13: Branch power flow capacity [MVA] in the power grid.

Branch	138 kV OHL ^a	138 kV cable (bus 6-10)	230 kV OHL ^a	Power transformer	New OHL ^a (bus 15-17 & 11-15)
MVA	175	175	500	400	500

^a OHL: Overhead line

Conventional generation

A conventional power plant is dispatchable, meaning that its electricity generation can be dispatched according to demand, within the technical limits of the plant. Nuclear and fossil fuelled thermal power plants and hydro power plants with reservoir capacity are examples of power plants that are dispatchable. The IEEE-RTS has an installed conventional power generation capacity of 3405 MW. Table 14 shows the type, capacity, Mean Time to Failure (MTTF), Mean Time to Repair (MTTR) and maintenance data for these units as specified in [10]. In this study an exponential distribution was chosen for the MTTF's and MTTR's. A maintenance schedule was developed for each unit based on the annual load variations, and this is specified in the rightmost column of Table 14. The maintenance schedule is

followed rigorously, independent of the power system state, apart from instances where the unit that is to be taken out for maintenance is already out due to a fault. In this case maintenance is omitted. This will seldom occur as the MTTF is significantly longer than the MTTR for most units.

Table 14: Type, capacity, reliability, maintainability and maintenance data for conventional generators (source: [10]), with assumed maintenance schedule.

Type ^a	MW (N ^b)	Bus(n ^c)	MTTF [h]	MTTR [h]	Maint. [weeks]	Maint. sched. [start week]
U12 – Oil/ST	12 (5)	15	2940	60	2	9,26,31,33,35
U20 – Oil/CT	20 (4)	1(2),2(2)	450	50	2	2,31,22,49
U50 – Hydro	50 (6)	22	1980	20	2	4,15,17,22,42,44
U76 – Coal/ST	76 (4)	1(2),2(2)	1960	40	3	28,46,6,24
U100 – Oil/ST	100 (3)	7	1200	50	3	2,19,50
U155 – Coal/ST	155 (4)	15,16,23(2)	960	40	4	5,19,23,46
U197 – Oil/ST	197 (3)	13	950	50	4	15,27,42
U350 – Coal/ST	350 (1)	23	1150	100	5	31
U400 - Nuclear	400 (2)	18,21	1100	150	6	9,37
<i>Total</i>	<i>3405</i>					

^a ST/CT: Steam turbine/Combustion turbine, ^b number of units, ^c number connected to bus

Wind Power Plants

All wind parks were connected radially to the IEEE-RTS grid. The connection point (bus) is referred to as the Point of Common Connection (PCC), see Figure 29. All wind parks are modeled as a real power injection, with a synchronous condenser (SynCon) at the PCC representing flexibility in reactive power output. The rating of the SynCon is $\pm 30\%$ of the installed wind power capacity for the AC wind parks and $\pm 100\%$ for the HVDC connected wind park.

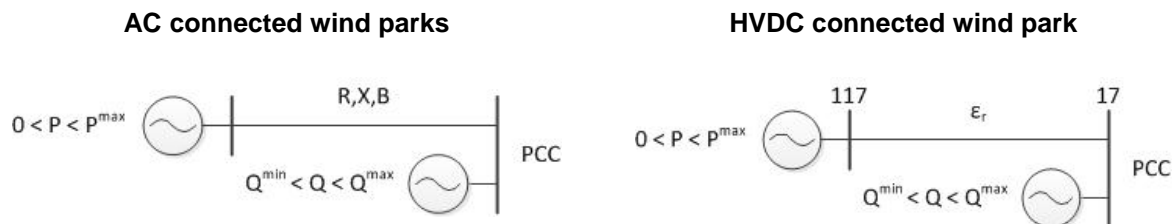


Figure 29: Modeling of wind parks and their connection to the IEEE RTS transmission grid. R: Resistance, X: Inductive reactance, B: Capacitive susceptance, ϵ_r : % energy loss in the AC/DC converters and HVDC cable.

B. Input Data on Load and Wind Power

Ref. [10] provides hourly load data. The peak, average and minimum load is 2850, 1752 and 966 MW respectively. Average energy consumption per year is 15.35 TWh. Figure 30 shows normalized load data for one year. The load resembles a winter peaking system, however with a high summer load as well. For the wind data it was decided to use one year of hourly values of aggregated wind generation in Denmark from the year 2011, which is available for free download from the website of the Danish TSO Energinet². The average wind capacity factor was found to be approximately 29%, or 2562 full load hours per year, based on the average installed capacity in Denmark in 2011 [13]. 2562 full load hours is in the high end compared with statistics from around the world [14]. Normalized wind generation data is displayed in Figure 30 and shows significant variations during all seasons, with power generation in general being higher during the winter season.

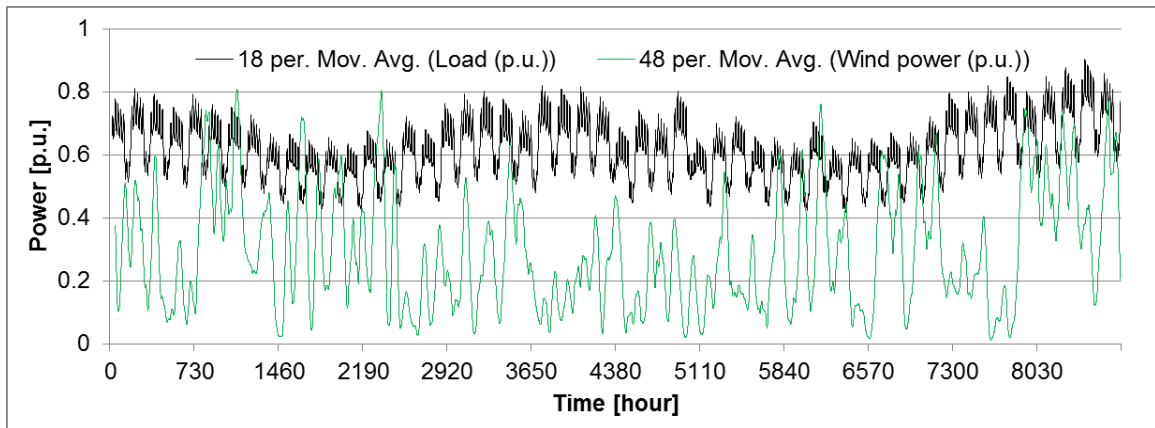


Figure 30: Time-series of load (black, 18 hour moving average) and wind power (green, 48 hour moving average)

C. Calculation of Reserves

A power system needs reserves to deal with contingencies and fluctuations in load and non-dispatchable generation. The total required reserve (R_t^{tot}) for time t is given as the sum of the contingency reserve (R_t^{cont}) and the operational reserve (R_t^{oper}):

$$R_t^{tot} = R_t^{cont} + R_t^{oper}$$

R_t^{cont} is typically given by the N-1 criterion, i.e. that the system should withstand the loss of a single major component without affecting electricity supply to customers. The N-1 criterion for generation is given by the largest generator in the system, so R_t^{cont} is fixed at 400 MW (see Table 14) throughout the simulation period. R_t^{oper} on the other hand varies with load and wind power generation. There is no commonly used method to determine the total required operational reserve in a power system. The alternative that was used in this study was to set it equal to 3 standard deviations (SD's) of the net load forecast error (σ_n):

² <http://www.energinet.dk/>

$$R^{oper} = 3\sigma_{nl} \quad \left(\sigma_{nl} = \sqrt{\sigma_l^2 + \sigma_w^2} \right)$$

where σ_l is the load forecast error and σ_w is the wind forecast error. R_t^{oper} thus covers a 99.7% confidence interval. Only negative forecast errors are interesting in this study as they specify the amount of reserves required to provide for a shortfall in wind power generation, a rise in load, or both. The negative forecast error for wind with 3 SD's of the wind forecast error is given by:

$$3\sigma_{w,t} = \min[P_{w,t}, 3\sigma_w^{max}]$$

where $3\sigma_{w,t}$ is the wind forecast error for time t , $P_{w,t}$ is the forecasted wind power for time t and $3\sigma_w^{max}$ is the forecast error as a ratio of the installed wind power capacity.

A load forecast error SD of 1.5% of forecasted load is used in this study, based on experience from larger system. The wind forecast error depends on many factors including number and size of wind parks, their spatial distribution, topography, wind resource and more. An ensemble forecast error SD is calculated using the method of cross-correlation of forecast errors between individual wind parks as described in [15]. The part of IEEE-RTS including wind power spans an area of roughly 150x200 km. Ref. [15] reports that day-ahead forecast errors for a single wind farm in Germany is 10-20% of installed capacity based on a study from 2005. The forecast error drops with lower lead time. In light of advances in wind forecasting and the move towards shorter time frames for scheduling and faster electricity markets it was decided to set the forecast SD for a single farm to 10% of its installed capacity. This value was used for all wind farms.

The resulting ensemble wind forecast error SD is shown in Figure 31 for increasing wind power penetration. The ensemble forecast error drops considerably as more wind parks are added. At 1050 MW the wind parks are located across a large part of the IEEE-RTS system and further installations only marginally decrease (and even increase) the ensemble forecast error. Figure 32 shows the resulting maximum reserve requirement for increasing penetration of wind power. The maximum operational reserve would be required at times of peak load combined with wind generation forecast exceeding 3 SD's of the wind forecast error. With no wind power it is sufficient to have up to 130 MW of operational reserves to cover the load variations. With 2500 MW wind the maximum operational reserve requirement has increased to around 460 MW.

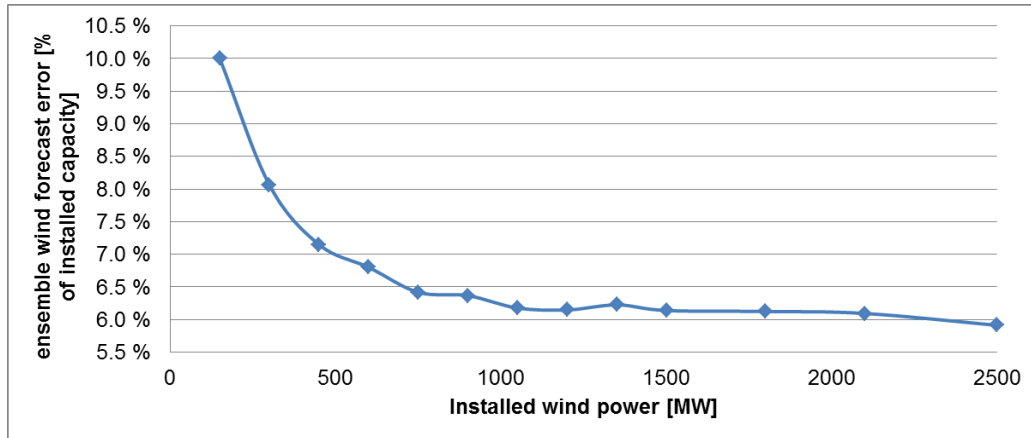


Figure 31: Ensemble wind forecast error SD in % of installed wind power capacity

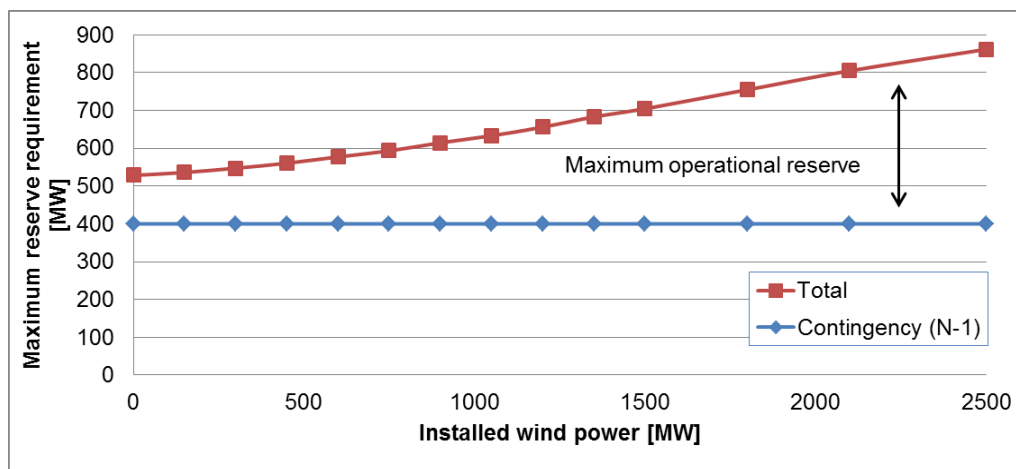


Figure 32: Maximum reserve requirement for increasing wind power penetration

D. Discrete Event Simulations

Monte Carlo simulations require in general a long simulation period to approach a stable result. The IEEE-RTS is known to be a generation limited system, and including failures on transmission lines and transformers would require a very long simulation period to reach a stable result. As the main focus of this study is to assess generation adequacy, it was decided to omit failures on transmission lines, transformers and substation related outages. Discrete events are thus generated by:

- Change in either load or wind generation (or both at the same time)
- Conventional generator taken out of operation due to fault or scheduled maintenance
- Conventional generator put back into operation after repair or maintenance

To reduce the number of events the load was grouped in four levels and wind generation in five levels, which give a total of 20 unique combinations of load and wind. The load and wind power duration curves and their respective discretized power levels are shown in Figure 33. Due to the discretization, the original time series of 8760 hourly events per year was reduced

to a time series of 1317 load-wind events per year (a reduction of 85%). The wind generation was normalized and distributed on the wind parks according to their installed capacity.

After some trials it was found that a simulation period of 100 years gave reasonably stable results. Almost 160,000 OPF simulations are performed in this period. Each 100 year simulation took on average about 8 hours on a 2.4 GHz Intel Core Duo CPU with 4 GB RAM.

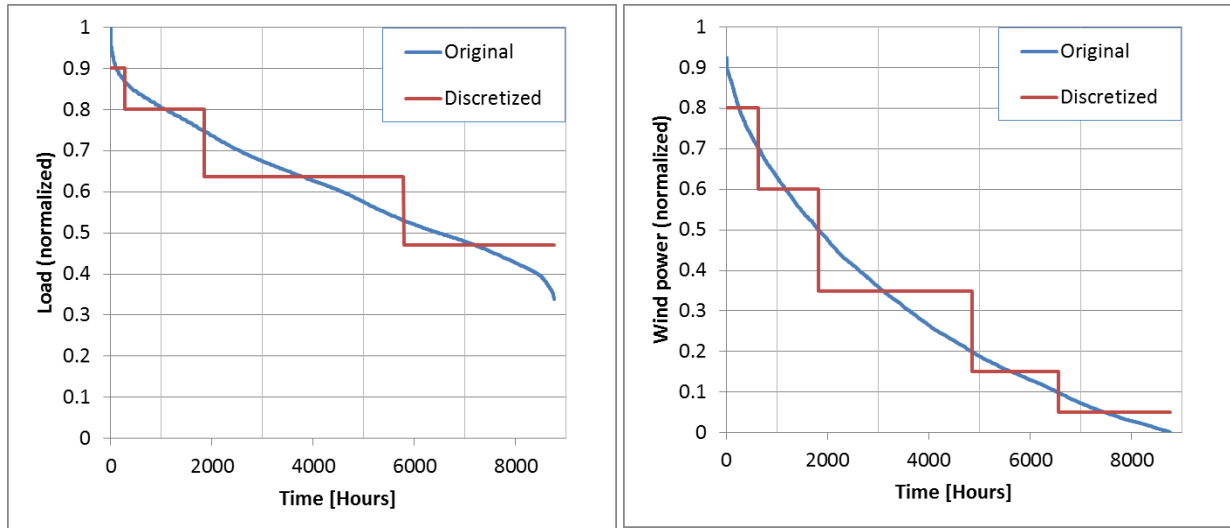


Figure 33: Duration curves for load (left) and wind power (right)

Four cases of wind power penetration were studied and compared to the reference case with no wind power. Main data for these cases are displayed in Table 15.

Table 15: Case studies of wind power included in the reference IEEE-RTS system

Case	1	2	3	4
Total wind power MW]	600	1200	1800	2500
Energy penetration [% of annual load]	10.0	20.0	30.0	41.7
Power penetration [% of peak load]	21.1	42.1	63.2	87.7
PCC (buses)	1,3,4,8	1,3,4,8, 19(1-2),13(1-2)	1,3,4,8, 19(1-2),13(1-2), 16,17(1),15	1,3,4,8, 19(1-2),13(1-2), 16,17(1),15, 24,17(2)

E. Evaluating Contribution to System Adequacy

In this study we measure generation adequacy by the *Energy Index of Reliability (EIR)*. The EIR states the ratio of load energy served to load energy demanded. It is calculated as follows, based on [16]:

$$EIR = 1 - \left(\frac{\overline{f_{ls}} \cdot \overline{P_{ls}} \cdot \overline{d_{ls}}}{\sum_{t=0}^{8760} P_d} \right)$$

where $\overline{f_{ls}}$ [yr^{-1}] is the average annual frequency of load shedding, $\overline{P_{ls}}$ [MW] is the average power not supplied during load shedding, $\overline{d_{ls}}$ [hours] is the average duration of a load shed and $\sum_{t=0}^{8760} P_d$ [MWh] is the annual sum of energy demand. Load shedding is enabled by letting all loads be fully dispatchable, with a corresponding VOLL set to 1000 €/MWh.

For the four cases with wind power, conventional generators were decommissioned until the EIR of a wind case approached that of the reference case. The choice of generators to be decommissioned was done qualitatively based on parameters such as start-up time, ramp rate and operating cost. Due to high flexibility and low cost, the six 50 MW hydro units were never considered for decommissioning. The four oil CT's are also quite flexible and were only considered as the last option.

Results

A. Contribution to System Adequacy

The EIR for the base case was calculated to be 99.970%. This means that out of a total electricity demand of 15.35 TWh per year, an average of 4.6 GWh would be shed due to generation inadequacy. For the four cases of installed wind power, Figure 34 shows the number and type of conventional power plants that could be decommissioned while maintaining the EIR at approximately 99.97%. The results show that the relative contribution to system adequacy from wind power drops as the wind penetration increases. This is in line with similar studies from real systems reported in [17]. The installed capacity, location in the grid, MTTF, MTTR, and scheduled maintenance (both time of year and duration) vary significantly for all the conventional power plants in the IEEE-RTS. It is therefore likely that other combinations of decommissioned power plants could yield similar results w.r.t. EIR.

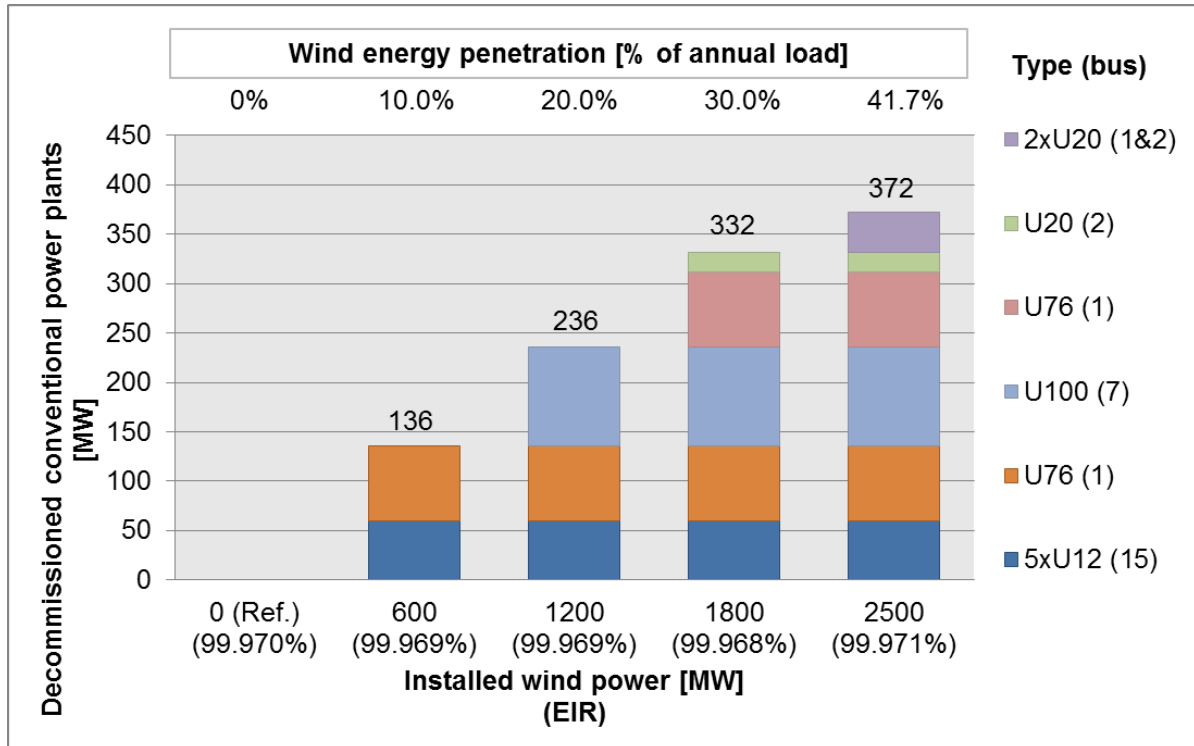


Figure 34: Conventional power plants that can be decommissioned while maintaining the EIR at approximately 99.97%.

B. Load Shedding

Table 16 shows the average annual frequency, duration and power of load shedding for the four cases compared to the reference case. The differences are small so it is not possible to conclude on any clear trend, but the results indicate that the frequency of load shedding increases slightly, whilst the duration decreases slightly. This could be explained by the fact that wind power varies more on shorter time scales (hours – days), while conventional power plants are down for considerably longer time after a fault or during maintenance (days – weeks).

Table 16: Average frequency, duration and power of load shedding

Case MW	Reference 0 MW	1 600 MW	2 1200 MW	3 1800 MW	4 2500 MW
Load wind shedding					
Avg frequency \bar{f}_{ls} [yr ⁻¹]	5.22	5.49	6.18	5.94	5.43
Avg duration \bar{d}_{ls} [h]	6.82	6.40	6.58	6.23	6.55
Avg power \bar{P}_{ls} [MW]	129.67	137.52	116.21	133.52	125.43

C. Violations of Total Reserve Requirement

Figure 35 shows that the total duration of hours where the available generation capacity in the system is less than the sum of load and total reserve requirement increases with increasing wind power penetration. When the reserve requirement is violated, the system will not be able to manage a N-1 contingency combined with a negative net load forecast error of more than 3 standard deviations. The severities of reserve requirement violations are also of importance. These were not quantified in this study.

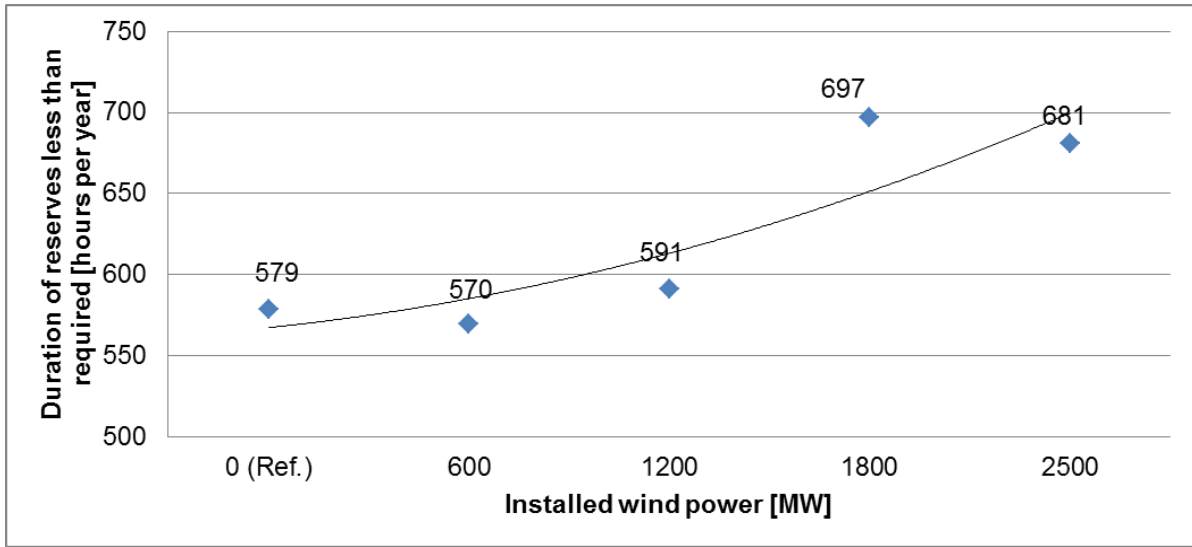


Figure 35: Hours per year where the available power capacity in the system is less than the sum of load and total reserve requirement.

Discussion

The following points highlight some important limitations of the PowerRisk tool:

- A power flow simulation assumes the system is in steady state. In fact, transients due to e.g. large generator or line trips could cause instability even if the post state is considered steady. A stability analysis needs to be done in order to test the system security for a given transient. It is worth noting that there exists no commercial tool for probabilistic security studies of power systems at the time being [11]. Including functionality to capture the more severe transients and performing stability analysis on these is a topic for further work.
- A power flow simulations is a snapshot of the system state and does not consider the history of events leading up to the current state. Hence, limitations on generator ramping and re-dispatch are not taken into account.
- Load shedding is conducted by dispatching loads downwards in a continuous manner. In reality loads would be shed in discrete steps. Therefore the results would tend to be optimistic w.r.t. load shedding. Block dispatching of loads would however

lead to a mixed integer problem which is substantially more complex and time consuming to solve than the linear OPF.

- The generator maintenance schedule lacks intelligence. A more sophisticated model for maintenance should be developed that postpones maintenance on main components if the system is severely stressed.

The following points list some main shortcomings of the conducted study and recommendations for studies of real systems:

- Correlation between wind and load is not captured, as the IEEE-RTS is a hypothetical power system. In studies of real systems it is paramount to use time-correlated wind and load data for the same area. Wind-load correlation could significantly impact wind power's contribution to system adequacy. See [17] for more discussion on this topic.
- Only one year wind data was used. In studies of real systems multi-year wind and load data should be used as especially wind can show high variations from year to year.
- The study assumed equal wind conditions on all wind parks in the system. Studies of real systems should use wind generation data for individual parks, or at least parks in relatively close proximity as this would more accurately capture the actual wind power in-feed at each bus and the resulting power flows in the grid. This is especially important if the transmission grid is constrained, and if the system under study spans a large geographical area.
- The generator maintenance schedule was based on the load alone. Optimizing the maintenance schedule based on forecasted net load (load minus wind power) would likely improve system adequacy.

Summary & Conclusion

The paper has presented a methodology to quantify wind power's contribution to system adequacy and use of reserves. The methodology is based on discrete event simulations combined with optimal power flow simulations, using a novel power system simulation and analysis tool developed at DNV. A case study is conducted, using the IEEE-Reliability Test System (RTS) as the model of the power grid, with wind generation data from Denmark. Results show that wind power's relative contribution to system adequacy drops as wind power penetration increases, in line with other reported studies. In addition, the violation of reserve margins tends to increase with increasing wind penetration. In studies of real system it will be important to use time-correlated wind and load data for the same area, preferably multi-year, and also wind generation for individual parks or park clusters in close proximity, to more realistically capture the power in-feeds and resulting power flows in the grid.

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Mixed-Criticality in Wind Power: The MultiPARTES Approach

David González¹, Jose Miguel Gárate², Anton Trapman², Lisandro Monsalve¹, Salvador Trujillo¹

¹ IK4-IKERLAN Research Centre, Spain

² Alstom Wind Power, Spain

dgonzalez@ikerlan.es

Abstract

The complexity of wind turbines has considerably increased in the last years. Recently, a substantial leap forward has come from off-shore technology. This new scenario is increasing the computational needs required in order to supervise, monitor and control the different subsystems within the wind turbine. Currently those computational needs could be addressed by different hardware platforms designed to meet specific requirements of a given subsystem, or by a unique hardware platform that would rarely meet all the requirements. This paper introduces the FP7 MultiPARTES project when applied to the off-shore wind power domain. MultiPARTES aims to provide a virtualization layer for heterogeneous multi-core processors to enable the use of a unique hardware platform that allows coexisting partitions (i.e. virtual machines) with different requirements in terms of criticality, real-time assurance, operating system or connectivity. Mixed-criticality refers to the integration in a platform of different applications with assorted levels of criticality. The suitability of the approach is demonstrated by the presentation of a real use case, in which a unique hardware platform supports three partitions with different criticality levels and real-time needs. This approach will bring important benefits such as the reduction of certification efforts, power consumption and size; the possibility to integrate third party applications without compromising the system, and many others that will be presented in detail. This use case demonstrates that the wind power domain will greatly benefit from the MultiPARTES approach, thus changing the way the control electronics are nowadays applied in the sector.

Keywords – Safety, Mixed-Criticality, Heterogeneous, Multi-Core, MultiPARTES

Introduction

The criticality level of an application is a classification of how severe a deviation of the intended behaviour is to the computer system and the environment in which it is located. The criticality level of a system is defined as the highest criticality of the jobs executed within it.

Wind turbines' control systems typically integrate a multitude of functionalities with potentially different criticality levels into a single system. Without appropriate preconditions, the integration of mixed-criticality subsystems can lead to a significant and potentially unacceptable increase of certification efforts. One approach to avoid the increased validation and certification effort is to incorporate mechanisms that establish multiple partitions with strict temporal and spatial separation between the individual partitions. In this approach,

subsystems with different levels of criticality can be placed in different partitions and can be verified and validated in isolation.

MultiPARTES [1] (Multi-cores PARTitioning for Trusted Embedded Systems) is an European research project funded by the Seventh Framework Program (FP7). The main goal of MultiPARTES is to support the engineering of mixed-criticality embedded systems based on virtualization techniques for heterogeneous multi-core processors. The starting point is XtratuM [2, 3], an open source hypervisor developed specifically for real-time embedded systems that is being increasingly used by the aerospace industry. Based on this approach, MultiPARTES will offer a rapid and cost-effective development of dependable real-time embedded systems integrating critical and non-critical applications on shared system resources.

The ultimate goal of MultiPARTES is to devise a comprehensive engineering methodology to take full advantage of partitioning of multi-core systems, thereby speeding up development and production of new highly dependable and secure applications. The results will be validated in several application sectors: off-shore wind power, industrial control, video surveillance, and space. However, the case study defined in order to validate the solution in the wind power domain has arisen as a very promising approach to implement future wind turbines' supervision and control systems, since it allows facing the newly emerged challenges.

This paper is structured as follows. Next section describes the challenges in the wind power domain. Then, the MultiPARTES approach is presented, as an introduction to describe the envisioned architecture for the future wind turbine supervision and control system based on this approach. Finally, last section draws some conclusions and outlook to future work.

Wind Power Challenges

The wind power domain is facing the market push towards off-shore operation. The road to off-shore introduces new technological challenges, stringent safety requirements and new standards to comply with. However, in many cases these new features have to coexist with the previously existing ones implementing less demanding requirements.

The off-shore operation requires high dependability. Dependability of a system is the ability to deliver justifiably correct services, and it comprises the following attributes: reliability, availability, maintainability, safety and security [6]. Next, they are elaborated in detail:

- *Reliability* is the probability that the system provides the specified services for a given amount of time, and its common metric is the mean time to failure (MTTF). As in many other industries, this metric is taking increasing importance in the wind power sector.
- *Maintainability* describes the effort required to repair a system after a failure occurred, and its common metric is the mean time to repair (MTTR). It has been a key factor in the on-shore platforms, but it becomes a critical issue in the off-shore wind turbines due to their remote location and reduced accessibility. The maintainability of a unique platform is usually better than the overall maintainability of several distributed platforms.

- *Availability* combines reliability and maintainability, and is the amount of time the system services are available. It can be expressed by the formula $A = \text{MTTF}/(\text{MTTF} + \text{MTTR})$. In the case of a wind turbine, the availability is a key indicator to evaluate the performance of a machine.
- *Security* is the enforcement of the availability, integrity and confidentiality properties against an entity that is intentionally malicious. Even if security has not been a big concern in the wind power industry, it must be considered in order to enforce the overall dependability.
- *Safety* is the reliability regarding critical failures, and is probably the most demanded attribute when the consequences derived from such a failure are extraordinarily catastrophic. This is the case of the wind turbine control, where a critical failure can lead to the destruction of the wind turbine, involving huge economic losses and eventually human damage. Since an off-shore wind turbine is usually much more expensive than a conventional on-shore platform, the relevance of the safety properties in the wind turbine supervision and control systems increases considerably.

Apart from dependability related challenges, there are some other challenges that the wind turbine supervision and control system (shown in Figure 36) must address, such as connectivity, certifiability, composability, or time-to-market.



Figure 36: Wind Turbine Supervision and Control System

Even if mixed-criticality is not a solution for many of the presented challenges, it is an approach to address them from a unique platform, thus reducing the complexity of the system. MultiPARTES approach targets mixed-criticality systems not only in the wind power domain, but also in other domains with similar needs. It aims at providing both the technology and the methodology to easily combine mixed-criticality systems over a virtualization layer that provides virtual machines and ensures temporal and spatial isolation between those partitions. There are other solutions in the market with similar features to

implement such a system, but MultiPARTES comprises some specific innovation points that are explained in the following section. Next section introduces the MultiPARTES approach.

MultiPARTES Approach

For reducing costs and afford many of the previously presented challenges, mixing different applications in a unique processing unit is advantageous. Unfortunately, it seems difficult to associate several applications with different levels of criticality. A possible solution is to design an architecture providing space and time separation between applications.

The TSP (Temporal and Spatial Isolation) is one of the most critical requirements for the MultiPARTES isolation layer implementation. The temporal isolation is achieved if the duration of every single action performed by applications in one partition is independent from actions performed by all other partitions. Spatial isolation (inter partition) must prevent all partitions from accessing memory or interfaces that are not in their a-priori known scope.

The isolation layer is the main component of the Trusted Computing Base (TCB) [5]. It provides the means to perform software partitioning while abstracting the underlying resources (e.g. hardware resources) for the software stack. This component is considered trusted, as it is the only component that sets up the isolation mechanism. The isolation layer includes three parts:

1. The partition manager or kernel, or the part that implements the isolation mechanisms;
2. The communication channels, which are the channels through which partitions can communicate, under the control of the TCB that enforces the security and safety policies;
3. The partition administration, which provides an interface to manage the kernel, in particular the partitions and the communication channels among them. It also provides the various system services needed to abstract the lower layers such as the device drivers.

The combination of the isolation layer with all lower implementation layers (i.e., hardware) makes up the trusted computing base (TCB). In order to implement the isolation layer of the TCB, different solutions are possible such as hypervisors. Hypervisor is the layer of software (or a combination of software/hardware) that, using the native hardware resources, provides one or more virtual machines.

Currently, there are some hypervisor implementations available in the market. However, MultiPARTES targets some innovation points, such as the multi-core heterogeneity, the open source implementation, and the support of a methodology and productivity tools to boost the time to market.

Figure 37 outlines the basic objective of the MultiPARTES approach. The virtualization layer allows changing the existing architecture, where some systems run on dedicated hardware platforms. In the envisioned architecture, all those systems share the same platform, while the TSP is ensured thanks to the partitioning kernel.

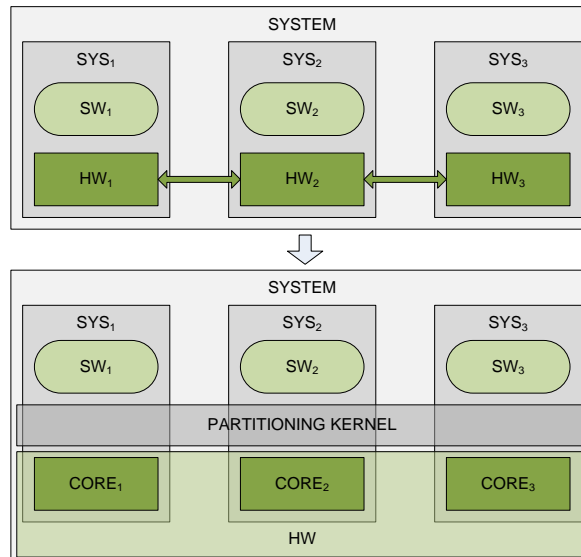


Figure 37: MultiPARTES Vision

In the following subsections, some of the MultiPARTES features are explained in detail.

A. Heterogeneous Platform

As previously explained, one of the key differences of the MultiPARTES approach with other virtualization solutions is the support for heterogeneous cores. Thanks to the heterogeneity, MultiPARTES can hasten the time to market of different applications, reduce the development costs by limiting the number of electronic control units (ECUs), raise the flexibility of the type of application supported and optimize the use of resources by using the most appropriate processor for each kind of application. In the MultiPARTES vision, at least one of the supported CPU cores must be oriented to host safety applications.

B. Execution Environments

One of the key benefits of a virtualization layer is the possibility to use different execution environments (i.e. operating system) in each partition. Thanks to this capability, the developer can select the most appropriate environment to meet the requirements of the functionalities allocated in a given partition. For instance, if the applications running on a partition do not need real time capabilities, the selected environment could be a general purpose operating system, thus widening the software off-the-shelf available to run on that partition. Obviously, the selection is bounded to the operating systems supported by the virtualization layer. To port a new operating system, some modifications need to be done in the operating system code, since MultiPARTES is based on para-virtualization.

C. Methodology and Tools Support

MultiPARTES proposes a MDE methodology. Developing critical systems is complex and needs a dedicated methodology. The methodology must follow the overall process and propose different tools in order to help the designers and to avoid errors. Some of the most representative features of the methodology that will be proposed in MultiPARTES are the V-Model shape (to ease the certification according to the safety standards), and the testing framework that will be provided.

Envisioned architecture

The main purpose of a wind turbine control system (also known as a supervisory system), is to supervise and control all the distributed subsystems that compose the wind turbine through a field bus interface. Strict real time constraints apply to the core of the supervisory system, which is a highly tested, robust and reliable embedded system based on a RTOS. The supervisory system also supports some functionality with no real time requirements, such as the Human Machine Interface (HMI) or the communications with the SCADA. The development and maintenance costs of these functionalities increase considerably when they are developed over a RTOS, which is not specifically oriented to contain this kind of services, and does not provide the facilities to implement them. MultiPARTES will solve this situation by allowing splitting the functionalities of the supervisory system into two different partitions.

The supervisory system also contains safety critical parts (e.g. the protection system in charge of ensuring that the design limits of the wind turbine are not exceeded). For this functionality to be included into the supervisory system platform, a third partition needs to be considered. The requirements of this partition are very different from other parts of the system, since the computational power required is much lower and a simpler microprocessor architecture to ease certification would be very valuable.

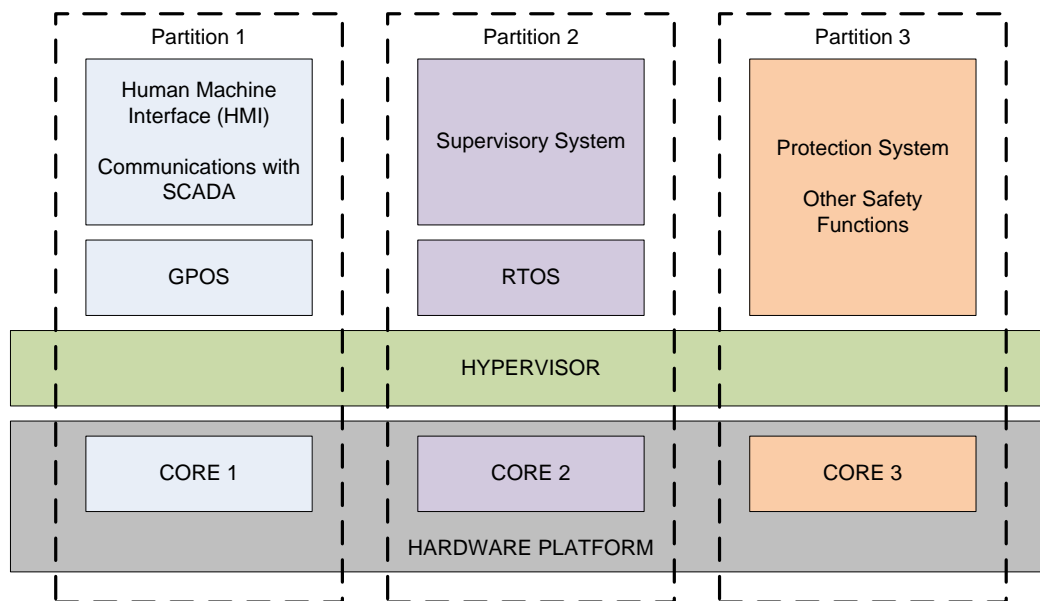


Figure 38: Envisioned architecture

MultiPARTES virtualization technology will offer to wind turbines' control systems a framework to easily combine these three sets of functionalities in different, highly isolated and securely intercommunicated partitions of the same hardware platform. Heterogeneity support would allow the use of a simpler and easier to certify core for the safe partition, while using a more powerful and extended core for the implementation of the other functionalities.

A. Benefits

The MultiPARTES approach can potentially bring many benefits to the wind power application sector. Firstly, there is an evident reduction of the required resources in terms of energy consumption, weight and volume, since a single device now integrates some functionality previously running in different hardware platforms. This reduction in the required resources positively impacts in the cost of the system (although this is not a major concern).

The integration of several subsystems in a unique platform also brings many benefits from the safety point of view:

1. System complexity is reduced, allowing distributed development teams.
2. Safety related functions are isolated, reducing the certification cost. The TSP allows ensuring independence among partitions with different levels of criticality, and enables modular-based independent verification of subsystems.
3. The reduction in the number of physical components such as cables and connectors (required to communicate subsystems in the absence of a virtualization solution) increases reliability, since this kind of components are prone to failure.
4. The validation of the solution can be performed more efficiently, obtaining clear advantages in the integration testing with respect to the situation where subsystems were implemented in different platforms.
5. The real time deterministic communications between subsystems (partitions) is easier, faster and abstracted from the application layer, since the virtualization layer now provides the communication services.
6. The inclusion of third party components does not compromise the safety objectives of the higher criticality partitions.

Other important benefits are the separation between real time and non real time functionalities, the componentization of the system to improve reusability, the easy distribution (and redistribution) of the computational resources, and the possibility to combine different operating systems adapted to subsystems requirements.

Figure 39 shows the relevance of all these benefits in the wind power domain and in other domains addressed in the MultiPARTES project.

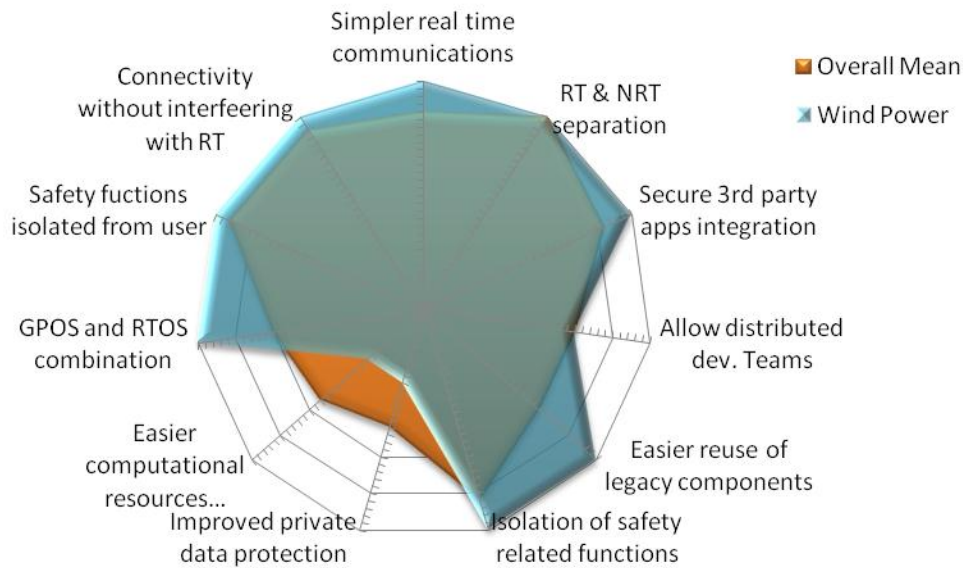


Figure 39: MultiPARTES benefits in the Wind Power domain

Summary & Conclusion

This paper introduced an approach for the engineering of off-shore wind power mixed-criticality systems based on heterogeneous multi-core and hypervisor technology. The necessity for this novel approach appears also in several industrial sectors, being especially relevant to the wind power domain. This setting is expected to become a typical scenario in the future of embedded systems engineering. Multi-core open source virtualization appears as a potential candidate solution for addressing future challenges, namely, reducing costs, power consumption, volume, and time to market, in an effective way.

We are currently working on defining the hardware platform and the multi-core hypervisor that will provide the basis described in this paper. We are also working on the metamodels and the tools that will empower the methodological approach. It will empower the productivity of the approach and ultimately enable its widespread adoption.

The virtualization technologies have been analyzed for many years in order to be included in the wind power embedded designs. MultiPARTES approach provides a solution which makes it feasible, bringing a number of significant benefits.

There are other virtualization solutions available in the market, but none of them fits completely with the requirements of the case study presented in this paper. The main reasons are the lack of support for heterogeneous multi-core platforms and the absence of a highly integrated set of tools to address the whole development lifecycle.

The use of heterogeneous multi-core virtualization is seen as an excellent candidate architecture to engineer the next generation of the wind turbine supervision and control system.

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Enabling Multi-Agent-Systems for wind turbine maintenance optimization through a common database

Khalid Rafik¹, Stefan Faulstich¹, Sebastian Pfaffel¹, Paul Kühn¹

¹Fraunhofer IWES, Kassel, Germany

Khalid.rafik@iwes.fraunhofer.de

Abstract

Maintenance management for wind turbines (WT) aims on the one hand at reducing the overall maintenance cost and on the other hand at improving the availability.

Although modern onshore WT attain high technical availability of up to 98 %, the evaluation of maintenance work in previous projects shows, that high WT availability requires additional maintenance work and costs. There is a considerable scope for optimizing reliability and maintenance procedures. A possibility therefore is to systematically make use of available knowledge and past experience. Thus, necessary steps have to be introduced for operation and maintenance of wind turbines to bring several readings together and to use them for improvements. At this point, information coming from databases, statistical methods as well as sound statements is essential. The consideration of several conditions e.g. weather conditions, power prognostics, stock keeping etc. are essential for optimal decisions. However, due to this enormous amount of information sophisticated tools are needed. This paper is going to show the possible application of high-performance computing methodologies, which may help wind farm operators (WFO) examining optimal maintenance strategies. The so called Multi-Agent-System (MAS) which is a new discipline in the world of Artificial Intelligence (AI) and the Data Mining (DM), which is a high-performance computing methodology used to observe and deduce hidden knowledge and logical dependencies of a great amount of data using several appropriate algorithms, should be investigated and a methodology for the use of AI in WT maintenance is proposed.

Keywords – Maintenance, Optimization, Artificial Intelligence, AI, Multi-Agent-Systems, MAS, Failure Database, Reliability, Availability, Data Mining, O&M

I. Introduction

The efficiency of WTs has been substantially improved in the past two decades in technical and economic view. The continuous development of wind power use permits purposeful advancements of the system technology in order to increase both efficiency and

performance of the turbines. However, earlier intensive and broad analyses in research projects [1], [2] show that the efficiency of modern WT's and their equipment units are not obligatory proportional to their reliability. However, today's organization of operating supervision and maintenance makes it still difficult to use the various experiences from the operating and historic data purposefully for future improvements of maintenance activities.

Up to now maintenance planning is usually still accomplished individually and intuitively by the WFO, although a multiplicity of different aspects (e.g. energy yield, availability, weather condition, personnel employment, material costs etc.) with partly opposite effects on availability and costs should be taken into account (Fig. 1) [3]. At present the WFO can't consider these different interests of the various aspects to the necessary extent for making sound decisions. There is a lack of tools that help to manage all those aspects simultaneously.

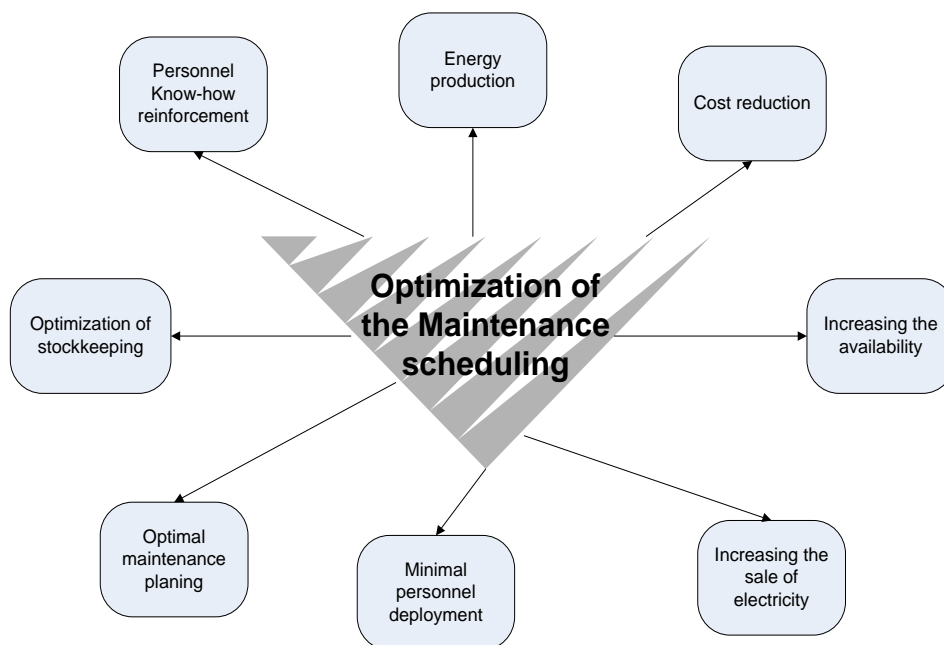


Figure 1: Competitive interests

In the past, only little focus was put in the use of methods and models of AI within the area of maintenance planning. The so called Multi-Agent-System (MAS), also known as Agent-Based-Modelling and Simulation (ABMS) can model the competitive aspects in such a way that the Agents negotiate quasi among themselves, which interests to be considered in decision-making [4]. Thereby each aspect is represented by an Agent. These Agents are

programmed to cooperate with each other in order to determine an optimal total conception. As a result of the Agents communication either a particular or several optimal alternative solutions can be suggested.

The project MAS-ZIH 'Use of Multi-Agent-Systems as Support for Reliability-Based Maintenance', which is funded by the German Federal Ministry of Environment, Nature Conservation and Nuclear Safety, is going to investigate the possibility of using AI in WT maintenance. The project duration is three years, starting last October 2011. Therefore, the findings presented here, represent the first steps in the field and will give an overview about the methodology and expected results.

II. Common (Failure) Database

A. The WMEP failure database

In the period from 1989 to 2006 a monitoring campaign, the scientific measurement and evaluation programme (WMEP), was conducted by ISET. During these 17 years 193.000 monthly reports of operation and 64.000 maintenance & repair reports from 1,500 WTs were collected and analysed [5]. The database of this programme contains a quantity of detailed information about reliability and availability of WTs and subassemblies, the preventive maintenance and repair costs, the failure causes, the failure effect and the removal of the malfunction. This provides one of the most comprehensive studies of the long-term behaviour of WTs worldwide.

Taking into account that activities are often carried out simultaneously for more than one subassembly (e.g. many replacements or many preventive tasks at the same time), will increase the amount of information concerning the maintenance tasks regarding a certain subassembly.

B. Parameters diversity

As described in [7] there are many parameters influencing the reliability characteristics of WTs e.g. the technical concepts, the external conditions, the power class of the WT, etc. For detailed analyses all these parameters must be taken into account. Fig. 2 shows the parameter diversity. One can see that even with a broad database like the WMEP failure database, with a breakdown in different groups a certain point is reached, where the statistical basis is getting insufficient. By the example shown the need for a broader database is getting clear.

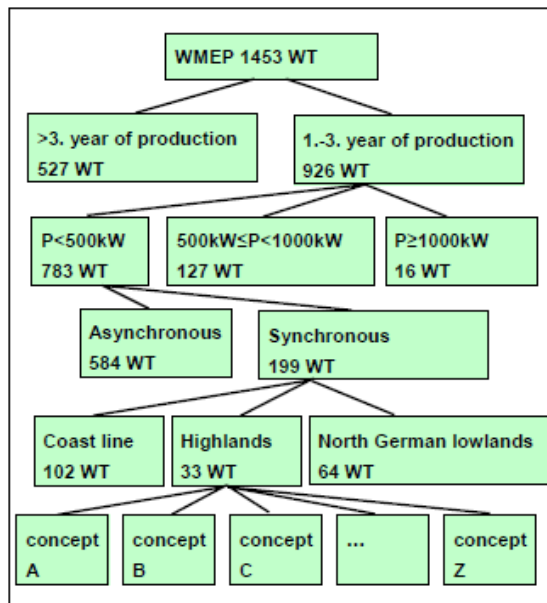


Figure 2 Parameters diversity

C. Research projects 'Improving Availability of WTs' and 'Offshore-WMEP'

In the research project 'Improving reliability of WTs' a consortium of owners, WFOs, services-providers and researchers exploit experience with WT operation more intensively. The focus of the project is on proposals for standardising data acquisition, data transmission and on a reliability characteristics library [6]. The project aims at improving reliability and as consequence availability and maintenance effort by the sub-goals:

- Standardising information structures
- Developing efficient management tools
- Improving strategies
- Optimising maintenance processes

Especially the standardising of information structures is fundamental for the use of experience gained.

Similar works in the offshore field is done in the project Offshore~OWMEP, where on the one hand fundamental questions concerning the use of offshore wind energy shall be answered by a general monitoring, and on the other hand operating experience shall be collected and analysed systematically in collaboration with operators and manufacturers. Gathering data will generate a large database which will contribute to political decision-making processes and facilitate further technological progress. The generation of a common

database will also, due to its size, enable statistically reliable predictions concerning the success of operational concepts

III. Methodology of Artificial Intelligence

The reliability-oriented maintenance of WTs relies particularly on the management and the evaluation of operating and maintenance data [2]. However, today's organization of data acquisition and data management by the WFO doesn't permit the easy use of experiences [8]. Additionally WFOs/service companies are missing tools and necessary information (e.g. failure statistics, weather forecasts, staff disposition, etc.), instructions and recommendations needed for their maintenance decisions.

A. Artificial Intelligence

By estimation of failure probabilities, remaining useful life and early recognizing of possible damages and errors as well as by using wind and power prognosis, maintenance tasks and procuring of spare parts could be better planned and unexpected stops could also be avoided. For an efficient maintenance planning the economic boundary conditions e.g. spare part and personnel costs or the temporal development of the fluctuating electricity tariff at the electricity market are to be considered. For the support of a foresighted maintenance strategy a MAS is to be developed, which uses the reliability characteristics and the cost information from WFO and weighs the competitive interests of the different aspects for the studied case and then suggests favoured maintenance measures for the decision-maker.

A schematic representation of the research within the work is shown in fig. 3, where different Agents manage different tasks. Some of them have the task to analyse the failure rates, while others regard weather and power forecasting, and the third category considers the question of cost of the whole maintenance process. A main goal thereby is to submit the WFO with an arranged list of requirements and proposals, on how the next maintenance should look like.

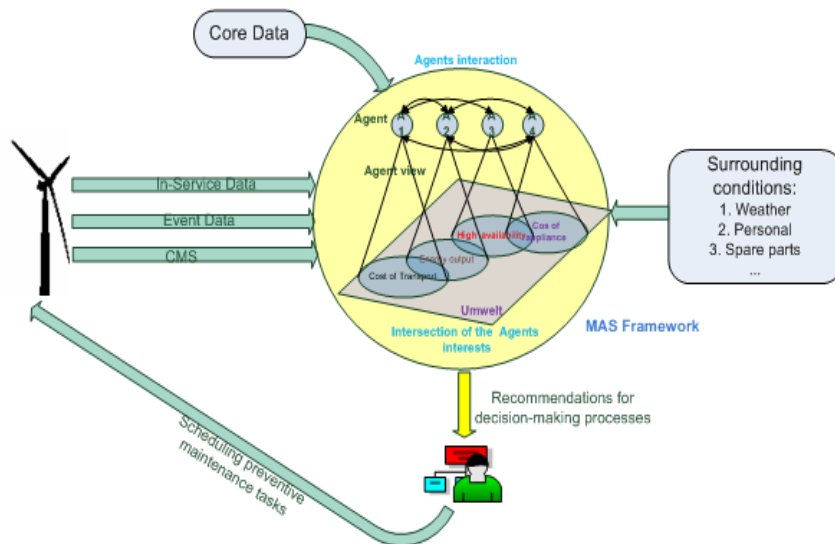


Figure 3: Use of MAS for improving the maintenance decisions

B. Hybrid approach of MAS and Data Mining

This approach consists of using the advantages of both technologies MAS and Data Mining. Before modeling the MAS-Model, some knowledge will be deduced by applying the Data Mining for the historic data of the WFO. This allows the Agents having some initial states, which they need in order to make sound simulation.

Data Mining

To understand the dependencies of historic preventive and repair maintenance, professional Data Mining Tools are used for this task. Such dependencies could identify the components that failed mostly and simultaneously with a given analyzed subcomponent or also possible cluster populations regarding the behavior of the subassemblies concerning the factors that play a dominant role on the failure of the analyzed component e.g. failure causes or downtimes etc. Fig. 4 shows an example for an extract of the Tree view that analyses the behavior and dependencies of the subassembly 'electric converter' for a WT type in the coast region of Germany. The figure shows that when this subassembly failed because of an 'Unscheduled repair after malfunction', and when the 'electric generator' was also affected at the same time and the whole downtime takes less than four hours, then the cause of this failure is usually 'malfunction of control system' otherwise it was 'other causes' and so on.

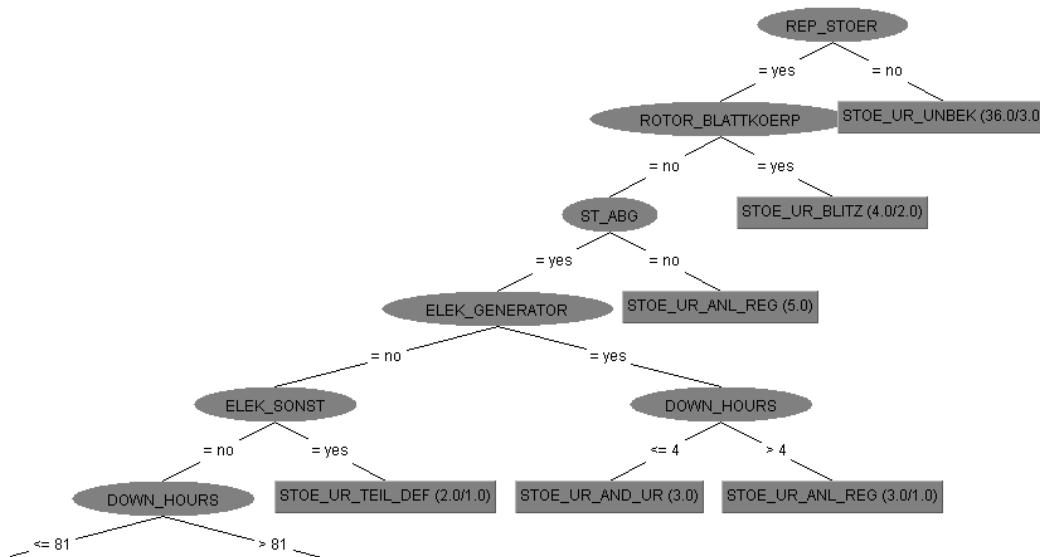


Figure 4: Extract of the Tree view ‘electric converter’

Fig. 5 shows the distribution of failure downtimes in function of failure causes for the same subassembly (‘electric converter’). The most frequent failure cause for failure with short downtimes duration between 0.5 and 79 hours (see the first bar in the x-axis; occurred 286 times) are ‘component wear’ (blue), ‘malfunction of control system’ (red) and ‘cause unknown’ (dark green). For failure with long downtimes duration in the interval [79h, 157h] (occurred 12 times) the first cause is ‘storm’ followed by ‘component wear’ and then ‘other causes’.

Identifying those dependencies for every subassembly will be decisive for improving the Agents intelligence as we will see later.

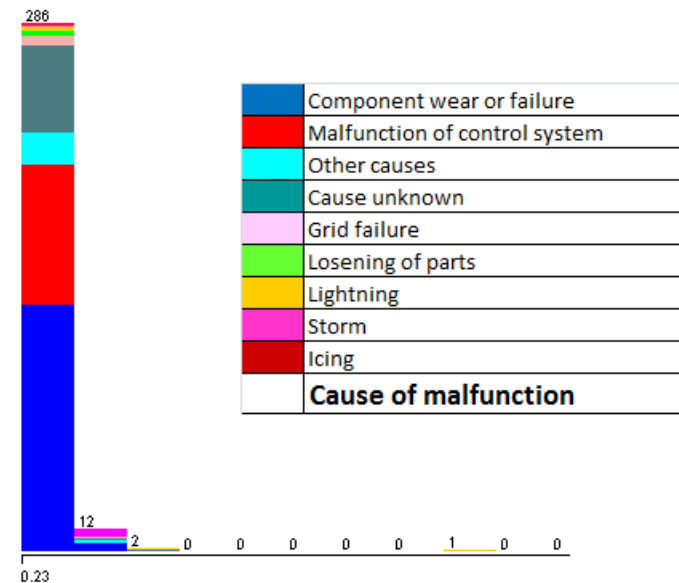


Figure 5: Distribution of failure downtimes in function of the failure cause for the subassembly 'electric converter'.

X-axis: downtime duration intervals

MAS

The approach of the dynamic modelling and simulation using MAS can make an important contribution in the area of maintenance of WT. In the past the analysis systems have integrated the reliability and maintenance aspects more and more in their evaluation. Several proven techniques already obtain considerably successes i.e. [13]. The existing methods for the modelling of availability/reliability can be divided into two groups: static and dynamic methods. [9].

Static methods require less information about the system characteristics than dynamic methods. A logical consequence of this decreased information requirement is their application in the early phases of a project. Although this knowledge base can be quite limited, static methods achieve good estimations for expected future availability and reliability of the object regarded [9]. In addition they are generally more intuitive and simpler in their application and attain faster results than their dynamic counterparts. The main impairment is their inability to treat time-based changes. Since the temporal sequences cannot be represented with static methods, they are generally less suitable for the modelling of maintenance activities, where maintenance planning and maintenance strategies are based mainly on time management [9].

Quite contrary to the static methods the strength of the dynamic methods lies in their ability to combine the temporal effects and the system developments. This characteristic makes the representation for system aging as well as the maintenance scheduling possible. Well-known examples of these dynamic methods are Markov Chains and Dynamic Fault Tree Analysis (FTA), which was already used successfully in the past [10]. Nevertheless these two techniques have large deficits, e.g. the Markov chains suffer an inevitable „condition explosion“, if they are used at large-scale systems and with mass data [1], while FTA already reach their borders, if the system models contain complex feedback loops [12].

Many investigations have been done in the area of dynamic methods using AI for optimizing the maintenance. Z. Tian, Y. Ding and F. Ding [1] review the current research status of maintenance of wind turbine systems, discuss the application of Artificial Neural Networks (ANN) based health prediction tools in that field, and develop a CBM approach for wind power generation systems to address maintenance planning issues.

E. Byon [14] examines the optimal repair strategies for wind turbines operated under stochastic weather conditions and lengthy lead times with the objective to minimize the expected average cost over an infinite horizon. He formulated the problem as an observed Markov decision process for these goals.

MAS is seen as an adequate technology for seeking out unknown and unexpected behavior of complex systems as well as for filtering the most important knowledge, those the WFO needs later for his maintenance planning [1]. Figure 6 illustrates a MAS platform with several modules. The Agents representing many objects (components, subassemblies, weather, spare parts stock keeping etc.) interact with each other, in order to find the optimal „solution“ for a given problem. The optimal replacement interval for a certain component or the best scenario of the team employment for tasks shared at different wind parks are examples for those solutions. The MAS regards several concepts in its analysis. It assigns Agents to analyse the so called Look-back database, in order to examine the past experiences, other Agents are assigned to analyse the Look-Ahead database for information and prognostics (e.g. the electricity tariffs of the next hour or days or also the weather prognostics as well as information concerning the stock keeping or to Team disposition).

C. MAS modules

An entire model based on the idea of categorizing the maintenance activities and the failed maintenance tasks in quality levels (Perfect, Imperfect, Minimal, Worse and Worst) introduced by [15] (see also [16] and [17]), where a Perfect maintenance task is a total replacement of wear out components or subassemblies, the Imperfect maintenance tasks are e.g. greasing, oiling, adjusting etc., and the Minimal maintenance task is reuse of old existing spare parts in another WT. These maintenance activity levels have an obvious impact not only on the health and useful life of the components and subassemblies but also

on future maintenance strategies. The whole model is created by taking into account the several factors i.e. financial, weather conditions and staff disposition (see Figure 6). It consists of five closely interconnected modules, which are the modules for: Failure-Rates, Production, Logistic aspects, Weather and Cost. This separation provides the option of using different simulation methods as well as an easy extension.

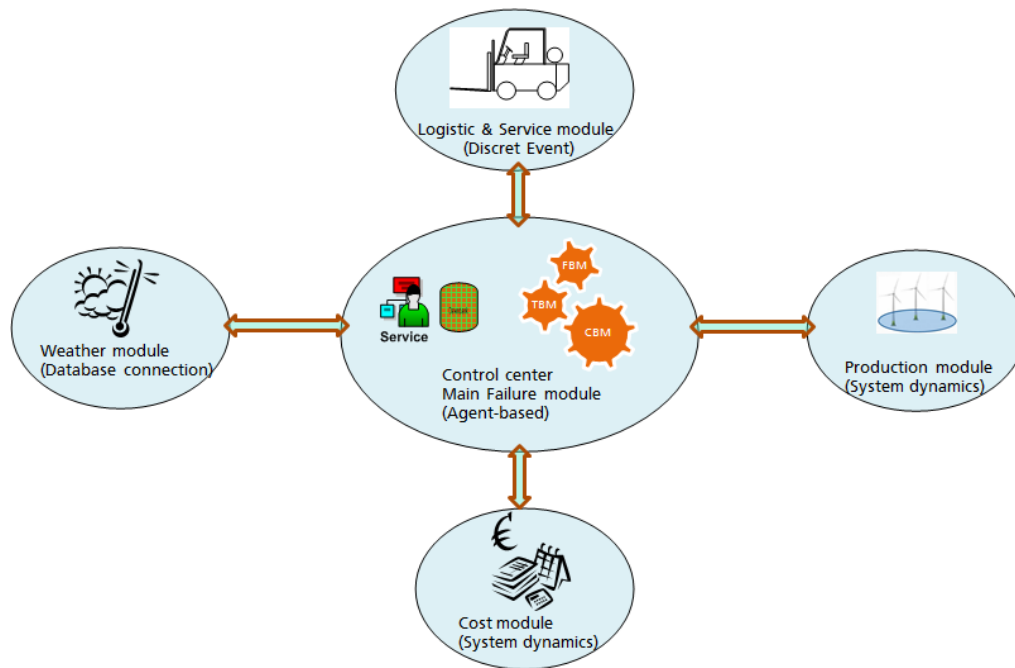


Figure 6: MAS Modules

The systems and their subassemblies will be represented by appropriate Agents, which have their own parameters and methods that enable them to act and react with their environment. Each one of those systems will represent an environment of its subassemblies (e.g. Generator-environment). All systems of the WT are in turn part of their own environment named WT-types-environment. The WTs at last are housed in the Farm-environment (see figure 7). This interconnected scheme makes the communication for homogeneous Agents inside an environment easier; the Agent is therefore more autonomous and self-directed, more flexible and possesses the ability to learn and to adapt its behaviours based on experience.

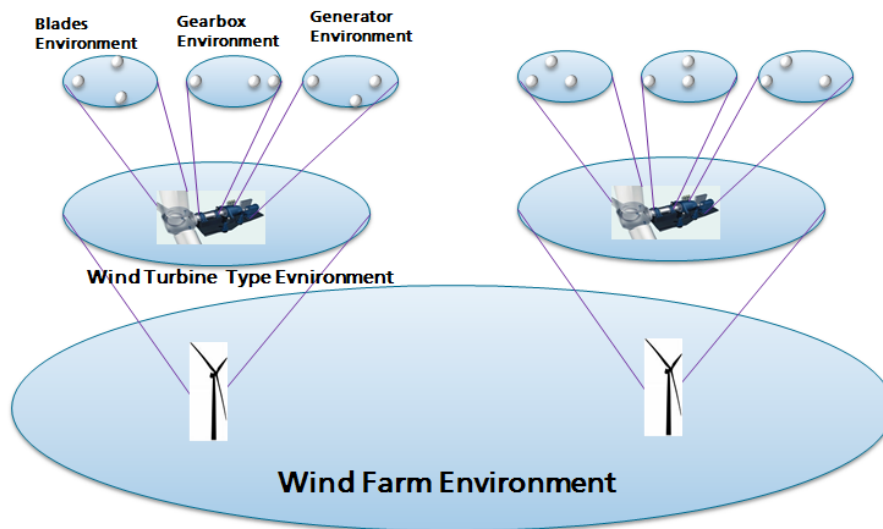


Figure 7: Interconnected Environment architecture

Based on the idea of characterizing the maintenance activities with quality levels, the Failure-Rate module triggers the interruptions in the Production module by message passing and calculates therefore the preventive maintenance and repair costs for the actual activity. The failure rates are calculated and updated after each maintenance activity using a developed algorithm, thus it provides the Agents with the necessary updated input parameters over the failure behaviour and failure frequency of the WT and their subcomponents continuously. For this first step, sources and information of the WMEP failure database are explored and analysed on their applicability for a showcase.

The Production module supplies the Agents with crucial information regarding the energy output and negotiate the best times of a maintenance measure based on power forecasts and SCADA data. The reliability-relevant SCADA operational data are prepared and analyzed on their applicability in a first step. Subsequently, the power forecasts are sighted, selected and forwarded as input parameters for the appropriate Agents. It provides the Logistic module with the needed information.

The development of the Weather module has the purpose to introduce weather conditions on basis of weather forecasts into maintenance planning. After identifying and evaluating existing meteorological aspects and their influence as well as relevant parameter for the maintenance, the results of the weather forecasts are made available as input data for the appropriate Agents.

Costs play a vital role in the maintenance organization; with the help of the Cost module it is to be demonstrated, how the cost can be considered during the reliability-oriented maintenance. Based on a commercial tool and several cost methods e.g. the methodologies of the 'Total Replacement Models' and the 'Partial Replacement Models' [218], which give an estimation of the optimal interval point to make a replacement with minimal costs, taken into account the labour costs, components costs and crane costs etc., all relevant cost parameters will be prepared as inputs for the appropriate Agents.

The consideration of logistics factors is indispensable for the optimization of maintenance strategies for WTs. The Logistic module will be interconnected with the Production module in order to manage the whole maintenance scheduling. Inside this module many input data (e.g. Spare parts stock keeping, components costs, transport cost etc.) will be available for the appropriate Agents, helping them suggesting optimal decisions.

IV. Conclusions & Conclusion

The necessity of building a common failure database as a basic condition for using Artificial Intelligence has been described in the contribution. Sophisticated Tools using AI are able to improve operating maintenance activities and help the WFO managing their task planning, taking into account several surrounding conditions in the analysis. For doing so a methodology has to be developed which was briefly described in this paper. The following points should be kept in mind when investigating the use of AI in WT maintenance:

- Establishing a common failure database is essential to achieve a suitable statistical basis for thorough analyses.
- Such a common failure database enables sophisticated approaches by analysing the history of the subassemblies in order to deduce and to forecast the failure behaviour of different subassemblies e.g. by using AI.
- Data mining and MAS are promising technologies in the field of maintenance of WT, but using them separately has some impairments. The use of a hybrid methodology to analyse dependencies between failure rates, weather conditions, logistics etc. is proposed.
- Using several cost optimization methods/algorithms will help by making the optimal decision in both reducing costs and improving availability.
- A balance between economic, reliability, availability and organisation issues needs to be achieved by the model developed.

V. Outlook

The use of MAS, which is based on a common failure database, is a part of the project MAS-ZIH funded by the German Ministry BMU. The five modules described in (3.3) will be combined and interconnected in this project to get a broad and comprehensive view of the several aspects of the maintenance process. This will help the WFO understanding the failure rates, costs, logistics, power outputs and weather dependencies and thereby to reach a decision for maintenance planning based on profound knowledge.

The project is now in the stage of developing the first main module; the Failure Rates module.

VI. Acknowledgements

The project MAS-ZIH 'Use of Multi-Agent-Systems as Support for Reliability-Based Maintenance' is it funded by the German Federal Ministry of Environment, Nature Conservation and Nuclear Safety.

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