Bayesian based Prognostic Model for Predictive Maintenance of Offshore Wind Farms

Masoud Asgarpour[1] and John Dalsgaard Sørensen[2]

[1,2]*Department of Civil Engineering, Aalborg University, DK-9220 Aalborg, Denmark*
jds@civil.aau.dk
mas@civil.aau.dk

[1]*Analytics & Asset Integrity Management, Vattenfall Wind, 1102BR Amsterdam, The Netherlands*
masoud.asgarpour@vattenfall.com

ABSTRACT

The operation and maintenance costs of offshore wind farms can be significantly reduced if existing corrective actions are performed as efficient as possible and if future corrective actions are avoided by performing sufficient preventive actions. In this paper a prognostic model for degradation monitoring, fault prediction and predictive maintenance of offshore wind components is defined.

The diagnostic model defined in this paper is based on degradation, remaining useful lifetime and hybrid inspection threshold models. The defined degradation model is based on an exponential distribution with stochastic scale factor modelled by a normal distribution. Once based on failures, inspection or condition monitoring data sufficient observations on the degradation level of a component are available, using Bayes' rule and Normal-Normal model prior exponential parameters of the degradation model can be updated. The components of the diagnostic model defined in this paper are further explained within several illustrative examples. At the end, conclusions are given and recommendations for future studies on this topic are discussed.

1. INTRODUCTION

The offshore wind energy is the fastest growing power sector in Europe, set to have a fivefold increase in installed capacity by 2030 (Tardieu et al. 2017). The offshore wind growth can be sustained only if offshore wind operation and maintenance (O&M) costs are reduced to their minimum, allowing utilities to operate profitable offshore wind farms in absence of government subsidies (Asgarpour 2018). The majority of O&M costs of offshore wind farms is caused by unplanned failure of wind farm components (Asgarpour & Sørensen 2015). The costs of unplanned failures can be reduced significantly if faults of wind farm components can be predicted, before they occur, or be detected, as soon as they occur and before they lead to a failure. In (Asgarpour & Sørensen 2018), a Bayesian diagnostic model for fault detection and condition based maintenance of offshore wind farm components is introduced. This paper focuses only on fault prediction or prognostics of offshore wind components.

In (Sikorska & Ma 2011), a thorough overview on knowledge-based, stochastic, Artificial Neural Network (ANN) and physical prognostic models applicable for Remaining Useful Lifetime (RUL) prediction of engineering assets is given. The authors in (Sikorska & Ma 2011) have concluded that mathematically or computing complexity limits current use of many prognostic approaches to industry practitioners. In (Novaes et al. 2018) and (Kandukuri et al. 2016), available prognostic models for gearbox, main bearing and blades of wind turbines are reviewed. Authors in (Novaes et al. 2018) have concluded that in contrary to diagnostics, very little attention has been given to the application of prognostic techniques in wind turbines. In (Lau et al. 2012), Hidden Markov Model (HMM), ANN and Particle Filter (PF) techniques for prognostic of offshore wind turbines are reviewed. Furthermore, in (Nielsen & Sørensen 2017), (Rasekhi Nejad et al. 2014) and (Griffith et al. 2014) case studies for prognostic of wind turbine blades, gears and bearings are given.

This paper demonstrates an applied and computationally inexpensive solution for prognostic and predictive maintenance of offshore wind components. In the followings, first degradation and remaining useful lifetime models are briefly discussed and then, within several illustrative examples a prognostic model for predictive maintenance of offshore wind components is outlined.

2. DEGRADATION MODELLING

Instead of probability of a failure, reliability of a component can be expressed by its degradation. According to EN 13306:2010 (Technical Committee CEN 319 2010), degradation is "*detrimental change in physical condition, with time, use or external cause*". Reliability of a component can be degradation based if the degradation of the component is gradual, observable and measurable.

In (Welte & Wang 2014), an overview of applicable models for degradation modeling of wind turbine components is given. The degradation level of a component can be estimated based on a physical or data-driven degradation model. Relevant physical models for degradation modeling of wind farm components are Paris' law for crack growth development (applied typically for degradation modelling of welded details in steel towers and monopiles, and in wind turbine blades) and S-N curves and the Palmgren-Miner's rule for fatigue assessment (applied typically for degradation modelling of foundations or drivetrain mechanical components).

Data-driven models for degradation modeling are statistical or Artificial Intelligence (AI) models based on continuous condition monitoring or inspection data. In (Schwabacher & Goebel 2007), a survey on AI models for prognostics is given. In contrary to AI models, statistical models are computationally inexpensive and are applicable to a wider range of component types and failure modes. In (Si et al. 2011), a comprehensive overview on statistical data-driven techniques for lifetime estimation of engineering assets is given.

Among statistical prognostic methods, exponential model is one of the most popular methods used (Li et al. 2015). In this paper, degradation of a component is assumed to be modelled using an exponential model:

$$D(t) = \beta(\mu,\sigma)\times e^{\alpha t} \tag{1}$$

The initial deterministic shape factor and normal distributed scale factor of an exponential degradation model should be first estimated. Once enough observations from degradation level or failures of a component are available, the initial shape and scale parameters can be updated.

2.1. Initial degradation model

In absence of sufficient operational data at the beginning of a wind farm lifetime, the initial values of shape and scale factors of an exponential degradation model of a repairable component can be estimated based on its average failure rate, which can be translated back into its mean time between failures ($^1/_\lambda = MTBF$). Then, a component failure can be expressed by its maximum degradation $D(t) = 1$ once its lifetime reaches $t \approx {}^1/_\lambda = MTBF$:

$$\begin{gathered} D\left(t \approx {}^1/_\lambda = MTBF\right) = 1 \xrightarrow{then} \\ D\left({}^1/_\lambda\right) = \beta(\mu,\sigma)e^{\frac{\alpha}{\lambda}} = 1 \xrightarrow{then} \\ \beta(\mu,\sigma) \approx \mu_\beta = {}^1\Big/_{e^{\frac{\alpha}{\lambda}}} \end{gathered} \tag{2}$$

Now that relation between shape and mean of the scale factor is known, it is sufficient to assume one of them. Based on the previous experience or experts' judgment, the shape factor of a component can be chosen. For instance, in Figure 1, the initial exponential degradation model for a component with an average failure rate per year equal to 0.05 based on three different shape factor assumptions is shown.

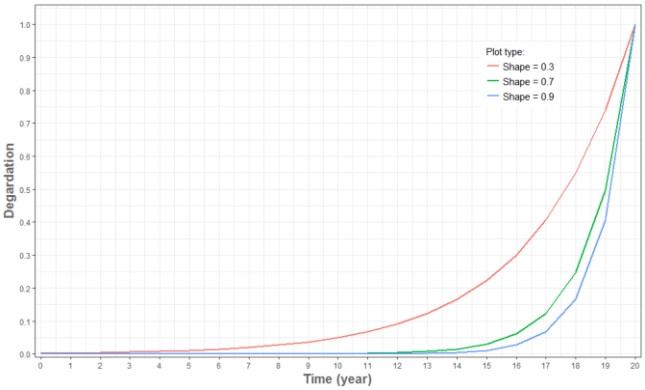

Figure 1. Initial degradation model of a component based on different shape factors assuming 0.05 as its failure rate per year

In Figure 1 it can be seen that a smaller shape factor (e.g. 0.3) results into more gradual degradation curve. On the contrary, a higher shape factor (e.g. 0.9) results into a less gradual degradation curve with sudden failure.

For instance, if based on the previous experience or experts' judgment, the shape factor of 0.7 be assumed for degradation model of the component shown in Figure 1, then according to Equation (2) the mean initial scale factor of this component can be calculated as $8.315E-07$.

The initial scale factor of an exponential degradation model can be assumed deterministic or if possible, based on the previous experience or expert's judgement, its standard deviation can be assumed. For instance, if the standard deviation of the scale factor be assumed as 5% of its mean, then the normal distributed scale factor can be defined as $\beta(8.315E-07, 4.157E-08)$. Now that both initial shape and scale factors are known, the initial or prior degradation model based on Equation (1) can be formulated as $D(t) = \beta(8.315E-07, 4.157E-08)\times e^{0.7t}$.

In Figure 2 the degradation model of the aforementioned component based on 1%, 50% and 99% quantiles of its stochastic normal distributed scale factor is visualized.

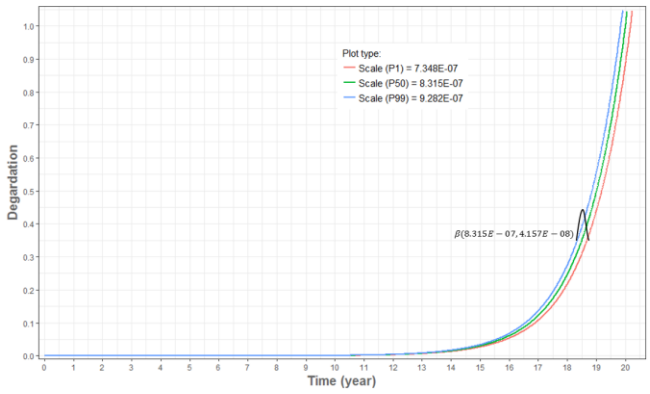

Figure 2. Initial degradation model of a component based on different scale factor quantiles assuming 0.7 as its shape factor

As shown in Figure 2, for a fixed assumed shape factor, smaller scale factors lead to slightly longer lifetime and higher scale factors lead to slightly shorter lifetime.

The uncertainty introduced by assuming the shape factor and standard deviation of the scale factor can be significantly reduced one sufficient observations for updating the initial model are available. The updating of initial shape and scale factors are discussed in the following section.

2.2. Updating the degradation model

The initial or prior degradation model of a component can be updated once observations on the degradation level of the component are available or once the component unexpectedly fails. The observations on the degradation level of a component can be based on inspection or condition monitoring data. Estimation of the degradation level of a component based on real-time condition monitoring data (such as vibration, temperature and oil particle data) is not further discussed here. In (Gebraeel et al. 2005), Bayesian updating of stochastic parameters of exponential degradation models based on real-time condition monitoring data is discussed in detail.

The degradation level of a component based on inspections can be determined using a Degradation Matrix. A degradation matrix is a catalogue for technicians to translate their observations during inspection of a component into discrete degradation levels of that component. If observed degradation of a component is known, then the mean observed scale factor of its exponential degradation model can be formulated as:

$$\beta(\mu,\sigma) \approx \mu_\beta = {}^{D}/_{e^{\alpha}} \xrightarrow{then} \mu_{\beta,observed} = {}^{D_{observed}}/_{e^{\alpha}} \quad (3)$$

In Table 1 an example of such a degradation matrix for wind turbine main bearings and monopiles is given.

Component	Observed Damage	Estimated Degradation
Bearing		
	No damage	0 - 0.2
	Micro pitting	0.2 - 0.4
	Debris damage	0.4 - 0.6
	Edge loading	0.6 - 0.8
	Cage damage	0.8 - 1.0
Monopile		
	No damage	0 - 0.2
	Coating damage	0.2 - 0.4
	Scour protection damage	0.4 - 0.6
	Substantial corrosion	0.6 - 0.8
	Substantial cracks	0.8 - 1.0

Table 1. Example of degradation matrix for inspection wind turbine of bearings and monopiles

For instance, if a technician observes minor coating damage on an offshore wind monopile, using the degradation matrix given in Table 1 she can translate it into degradation level of 0.25. Then, based on Equation (3) and assuming 0.7 as the shape factor, the associated mean scale factor to this degradation level is 0.124.

In order to take into account the uncertainty of inspection or condition monitoring based observations, a hybrid of observations from different sources can be used. Then, the scale factors estimated based on these inspections can be fitted to a normal distribution and consequently, observed mean and standard deviation of the observed scale factor can be determined. For instance, besides the inspection results, the degradation level of the same monopile based on the accumulated fatigue calculated from structural health monitoring data can be estimated. Then, the observed scale factor can be used to updated the prior one estimated in section 2.1.

2.2.1. Updating of scale factor

As discussed above, once by inspections and/or condition monitoring data the degradation level and associated observed scale factor of a component is known, the posterior scale factor of that component's degradation model can be calculated. The posterior distribution of a normal distribution is also a normal distribution. According to the Bayes' rule and Normal-Normal model (Jacobs 2008), the parameters of the posterior distribution of a prior normal distribution given an observation can be calculated using Equations (4) and (5):

$$1/\sigma^2_{Posterior} = 1/\sigma^2_{Prior} + 1/\sigma^2_{Observed} \quad (4)$$

$$\mu_{Posterior} = \frac{1/\sigma^2_{Prior}}{1/\sigma^2_{Posterior}} \times \mu_{Prior} + \frac{1/\sigma^2_{Observed}}{1/\sigma^2_{Posterior}} \times \mu_{Observed} \quad (5)$$

According to Equation (4), the posterior precision of a normal distribution is equal to the summation of its prior and observed precisions ($1/\sigma^2$). Furthermore, according to Equation (5), the posterior mean of a normal distribution is equal to the summation of its weighted prior and observed means. For instance, if based on several observations the degradation scale factor of the component shown in Figure 2 is observed as a normal distribution with $\mu_{Observed} = 1.2E-6$ and $\sigma_{Observed} = 1.2E-7$, then according to Equations (4) and (5) the posterior degradation scale factor of this component can be formulated as $\beta(8.71E-7, 3.928E-8)$.

In Figure 3, the prior, observed and posterior normal distributed scale factors of the degradation model are visualized.

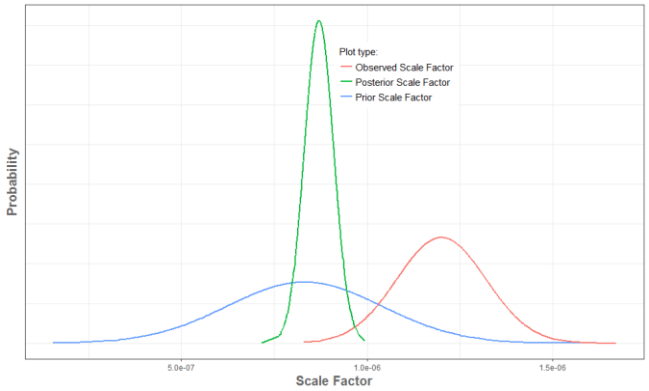

Figure 3. Posterior scale factor of a component plotted against prior and observed scale factors

Similarly in Figure 4, the prior, observed and posterior degradation of this component based on its Bayesian updated scale factor is visualized.

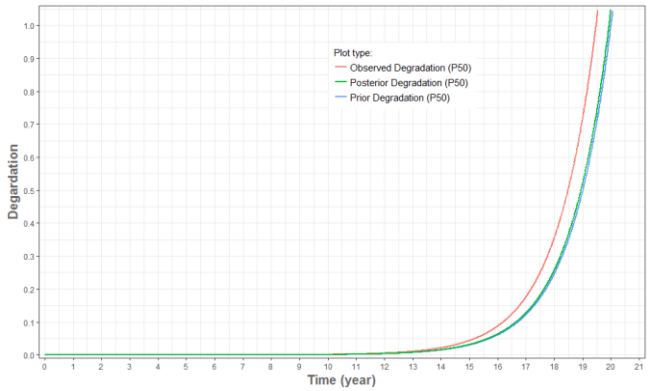

Figure 4. Posterior degradation of a component based on its updated scale factor

It should be noted that in Figure 4, only 50% quantile of the degradation graphs is visualized.

2.2.2. Updating of shape factor

The shape factor of an exponential degradation model can also be updated once an unexpected failure (not expected by its degradation curve) is occurred. If a failure occurs at time t, then the updated shape factor can be calculated as:

$$D(t) = \beta(\mu,\sigma)e^{\alpha t} = 1 \xrightarrow{then} \alpha = \frac{-\ln \mu_\beta}{t} \quad (6)$$

For instance, if it is observed that the component shown Figure 2 with shape factor of 0.7 has failed unexpectedly at year 18, then according to Equation (6) the updated degradation shape factor of this component is 0.78.

Similar to updating method of scale factor, the shape factor can also be updated within a Bayesian model. In that case, the shape factor should be modelled as a stochastic variable, perhaps fitted to a Weibull distribution. Then, the prior shape factor can be updated based on observed failures to determine the posterior shape factor. This method is not further discussed in this paper. Since both updated shaped and scale factors are known, the updated or posterior degradation model for this component can be formulated as $D(t) = \beta(8.71E-7, 3.928E-8) \times e^{0.78t}$.

In Figure 5, the 50% quantile posterior degradation of this component based on its updated shape and scale factors is shown.

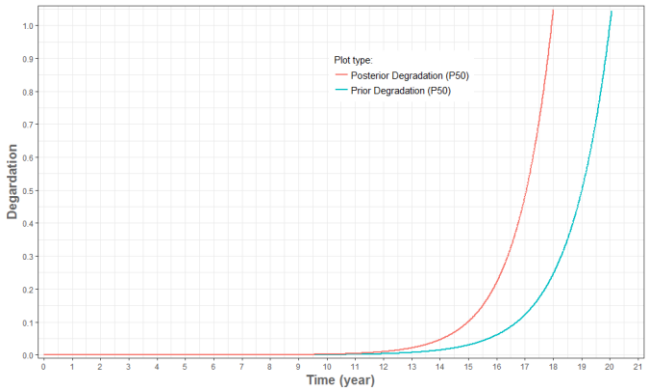

Figure 5. Posterior degradation of a component based on its updated scale and shape factors

Now that degradation modelling of a wind farm component is known, the remaining useful lifetime of a component at any given time can be calculated.

3. RUL MODELLING

Once the degradation of a component reaches its maximum, that component can be considered as failed. Based on this statement, the Remaining Useful Lifetime (RUL) of such a component at a given time t can be calculated as:

$$RUL(t) = \left(^{-\ln \beta(\mu,\sigma)}/_{\alpha}\right) - t \qquad (7)$$

The RUL estimation of a component is of interest especially when the degradation level of that component is verified by observations. As an example, the 50% quantile of the remaining useful lifetime of a component with the posterior degradation shown in Figure 5 at year 15 using Equation (7) can be calculated as 2.94 years.

According to this remaining useful lifetime estimation, this component can operate for another 2.94 years before its failure. This value calculated for 50% quantile is the mean of RUL at year 15. In order to determine the uncertainty associated with this RUL prediction at 15 years of lifetime, the RUL(15) for all quantiles should be calculated.

For instance, in Figure 6 the RUL of this component at year 15 based on all quantiles is visualized.

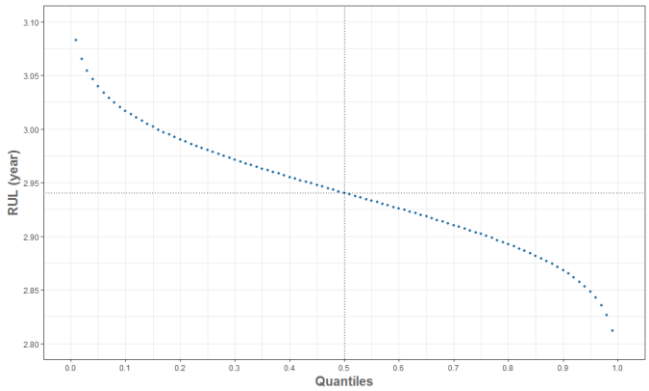

Figure 6. Uncertainty in RUL prediction at year 15 for the component shown in Figure 5

In Figure 6, it can be seen that the RUL predication at year 15 deviates from approximately 2.8 years to 3.1 years. This uncertainty can be translated into standard deviation of 0.056 years. Similarly, in Figure 7, five quantiles of the remaining useful lifetime of this component plotted against its lifetime and degradation level are shown.

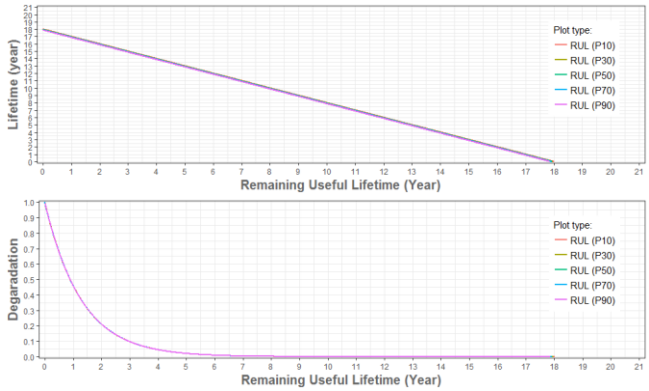

Figure 7. Remaining useful lifetime of a component plotted against its lifetime and degradation level

From Figure 7 the variation between different remaining useful lifetime quantiles for a given time is not very visible since the standard deviation of the RUL for this example (about 0.05 year) is too small for yearly scale of this graph.

4. PROGNOSTIC MODEL

Now that both degradation and RUL models for offshore wind components are known, a prognostic model for fault prediction, degradation monitoring and predictive maintenance of offshore wind components can be developed. In Figure 8, a framework of a prognostic model with Bayesian updating for offshore wind farms is outlined.

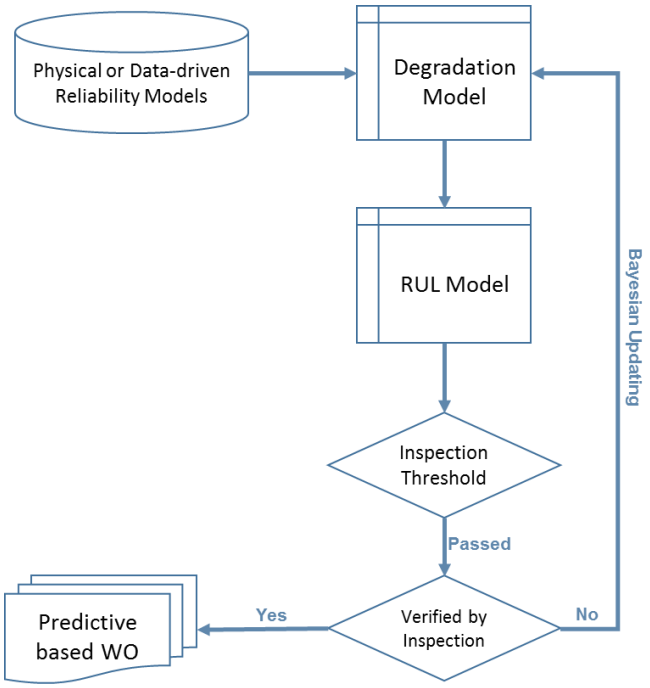

Figure 8. Framework of a prognostic model with Bayesian updating for offshore wind farms

The degradation and RUL models required for this prognostic framework are already discussed in the previous sections of this paper.

As seen in Figure 8, once degradation and RUL models of offshore wind components are established, inspection thresholds should be defined to initiate inspections for validation of the predicted degradation of components. If based on an inspection it is proven that the predicted degradation level is correct, then a predictive maintenance work order should be created to reduce the degradation of the component or to avoid its future faults. On the other hand, if based on an inspection it is proven that predicted degradation level of the component is not correct, then the observed degradation level should be used to update the initial or prior degradation and RUL models, as discussed in section 2.2 of this paper.

Validation of the predicted degradation level can be done based on the degradation matrix shown in Table 1. For instance, the predicted degradation level of a component is considered proven only if it is within 10% of the observed degradation, determined by using the degradation matrix within an inspection.

The inspection thresholds can be defined based on a degradation limit, based on a RUL limit, or based on a hybrid of these two. The inspection thresholds should be defined in a way to minimize the number of false predictions and to comply with defined O&M costs or wind farm availability targets.

4.1. Degradation based threshold

The degradation based inspection thresholds are triggered once the predicated degradation level of a component goes over a limit, such as 0.7 of the 50% quantile degradation curve. If a prognostic model opts for a degradation based threshold, then an inspection should be done once a component lifetime reaches:

$$D(t) = \beta(\mu,\sigma)e^{\alpha t} \xrightarrow{then} t = \frac{\ln(D(t)/\beta(\mu,\sigma))}{\alpha} \quad (8)$$

For instance, if a prognostic model for the component shown in Figure 5 opts for 70% of the degradation at 50% quantile as the inspection threshold, then according to Equation (8) an inspection for this component should be created once its lifetime reaches 17.6 years.

If the inspection outcome proves that the predicted degradation is correct, then a predictive work order should be created. At this time, according to Equation (7) the remaining useful lifetime of this component is only 0.29 year or three and half months.

As discussed earlier in section 3 of this paper, the uncertainty or standard deviation of these estimations can be determined by calculating these values for all quantiles.

It is possible that three and half months is not enough time to execute this predictive work order, while keeping work order execution costs to its minimum, especially if it is in winter season when long waiting times due to harsh offshore weather condition is expected. In order to avoid this situation, a prognostic model can opt for a RUL based inspection threshold.

4.2. RUL based threshold

The RUL based inspection thresholds are triggered once the predicated RUL of a component goes below a limit, such as 0.5 year of the 50% quantile RUL curve. If a prognostic model opts for a RUL based threshold, then an inspection should be done once a component RUL reaches:

$$t = ({}^{-\ln\beta(\mu,\sigma)}/_{\alpha}) - RUL(t) \quad (9)$$

or once the degradation of the component becomes:

$$D(t) = \left(\beta(\mu,\sigma)e^{\alpha t}\middle| t = ({}^{-\ln\beta(\mu,\sigma)}/_{\alpha}) - RUL(t)\right) \quad (10)$$

For instance, if a prognostic model for the component shown in Figure 5 opts for half a year or six months RUL (at 50% quantile) as the inspection threshold, then according to Equations (9) and (10), a predictive work order for this component should be created once its lifetime reaches 17.39 years or once its degradation becomes 0.68.

Similarly, as discussed earlier in section 3 of this paper, the uncertainty or standard deviation of these estimations can be determined by calculating these values for all quantiles.

If an inspection threshold is RUL based, then it can be ensured that sufficient time for preparation and execution of follow up predictive work orders is available. However, RUL based thresholds do not directly consider the degradation level of a component, which can result into non-repairable damage to some components.

4.3. Hybrid threshold

The optimal inspection threshold for wind farm components is a hybrid of degradation and RUL based thresholds to ensure that always sufficient time is available for cost-effective predictive maintenance of components and at the same time, the damage of the component is not very severe and still it can be easily repaired without bearing much costs.

For instance, a hybrid inspection threshold for a component can be 70% of degradation and 6 months RUL both at 50% quantiles, whichever occurs first. In Figure 9, this hybrid of degradation and RUL based thresholds for prognostic of the component with posterior degradation curve given in Figure 5 is visualized in red and green dotted lines.

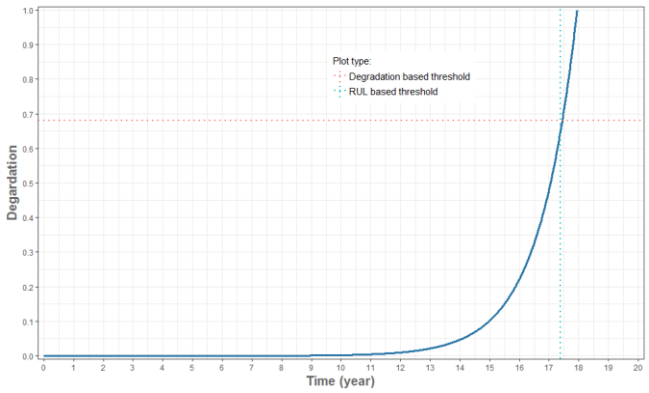

Figure 9. Hybrid degradation and RUL based inspection thresholds for prognostic of offshore wind components

The hybrid inspection thresholds can be updated once based on the inspection results they proven to be insufficient.

5. CONCLUSIONS

The prognostic model defined in this paper is based on degradation and remaining useful lifetime of wind farm components. The degradation model defined here is based on an exponential model, which initial values of its deterministic shape factor and normal distributed stochastic scale factor can be determined by using the average failure rate of a component. Once sufficient inspection or condition monitoring based observations on the degradation level of a component is known or once a component unexpectedly fails, the initial shape and scale factors can be updated to determine the posterior degradation model. The uncertainties associated with assumed initial exponential parameters of the degradation model can be significantly reduced once sufficient observations for Bayesian updating of the model are available. The more this prognostic model is used in practice, the less the associated uncertainties are.

In future studies on this subject, the exponential degradation model in this diagnostic model can be replaced by a physical or AI degradation model to increase the model accuracy. Relevant physical models for degradation modeling of wind farm components are Paris' law for crack growth development (applied typically for degradation modelling of welded details in steel towers and monopiles, and in wind turbine blades) and S-N curves and the Palmgren-Miner's rule for fatigue assessment (applied typically for degradation modelling of foundations or drivetrain mechanical components). Additionally, similar to Bayesian updating of the degradations scale factor, the degradation shape factor can be modelled as a Weibull distribution and be updated once some component failures are observed.

In the prognostic model defined in this paper a hybrid of degradation and remaining useful lifetime inspection thresholds can be used to initiate an inspection for validation of the model results. Once an inspection is triggered, if using a defined degradation matrix, it is proven that the predicted degradation is not correct, based on the observed degradation during the inspection the scale parameters of the exponential degradation model can be updated. However, if by an inspection it is proven that the predicted degradation of a component is indeed correct, then a predictive based work order is created to reduce the component degradation or to avoid its future faults.

Instead of using one set of thresholds followed by one predictive maintenance strategy, the application of multiple thresholds followed by several different preventive maintenance strategies based on different quantiles (uncertainty levels) of degradation and/or remaining useful lifetime curves can be investigated. Furthermore, within a Bayesian decision network, all possible unknown random outcomes of all possible future inspections can be modelled and then, optimal O&M strategy based on given cost or availability targets at any given time stamp can be estimated. In (Sørensen 2009) a framework for such a Bayesian decision model is defined and in (Nielsen 2013) and (Nielsen & Sørensen 2014) several case studies for risk based Bayesian decision models are presented.

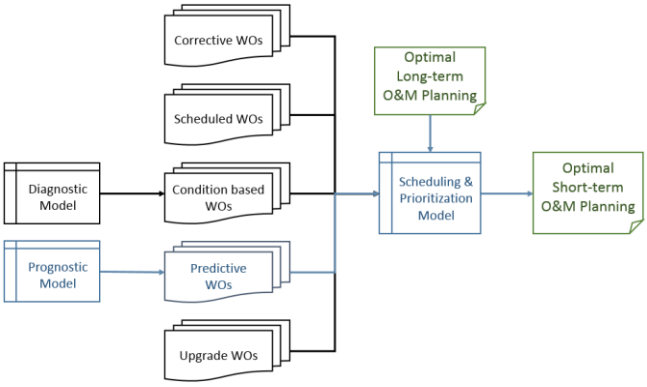

Figure 10. Framework for optimal short-term O&M planning of offshore wind farms

Once based on the prognostic model defined in this paper optimal predictive work orders are created, a work order scheduling and prioritization model such as the one shown in Figure 10 should be used to determine optimal short-term O&M planning for all outstanding work orders in a working shift, including corrective, scheduled, condition based and upgrade work orders. In (Asgarpour 2018) scheduling and prioritization of offshore wind maintenance work orders is further discussed.

NOMENCLATURE

D(t)	exponential degradation of a component at time t
α	deterministic shape factor of D(t)
β(μ, σ)	normal distributed scale factor of D(t) with mean (μ) and standard deviation (σ)
λ	average failure rate of a component
MTBF	mean time between failures of a repairable component
μ_{Prior}	mean of the prior scale factor
σ_{Prior}	standard deviation of the prior scale factor
$\mu_{Observed}$	mean of the observed scale factor
$\sigma_{Observed}$	standard deviation of the observed scale factor
$\mu_{Posterior}$	mean of the posterior scale factor
$\sigma_{Posterior}$	standard deviation of the posterior scale factor

REFERENCES

Asgarpour, M., 2018. *Risk and Reliability based O&M Planning of Offshore Wind Farms*. Aalborg University.

Asgarpour, M. & Sørensen, J.D., 2018. Bayesian based Diagnostic Model for Condition based Maintenance of Offshore Wind Farms. *Energies*, 11(300).

Asgarpour, M. & Sørensen, J.D., 2015. State of the Art in Operation and Maintenance Planning of Offshore Wind Farms. In *European Safety & Reliability Conference (ESREL)*. London, pp. 1119–1125.

Gebraeel, N.Z. et al., 2005. Residual Life Distributions from Component Degradation Signals : A Bayesian Approach Residual-life distributions from component degradation. *IIE Transactions*, 37, pp.543–557.

Griffith, D.T. et al., 2014. Structural health and prognostics management for the enhancement of offshore wind turbine operations and maintenance strategies. *Wind Energy*, 17, pp.1737–1751.

Kandukuri, S.T. et al., 2016. A review of diagnostics and prognostics of low-speed machinery towards wind turbine farm-level health management. *Renewable and Sustainable Energy Reviews*, 53, pp.697–708. Available at: http://dx.doi.org/10.1016/j.rser.2015.08.061.

Lau, B.C.P., Ma, E.W.M. & Pecht, M., 2012. Review of Offshore Wind Turbine Failures and Fault Prognostic Methods. In *Prognostics & System Health Management Conference*. Beijing: IEEE.

Li, N. et al., 2015. An Improved Exponential Model for Predicting Remaining Useful Life of Rolling Element Bearings. *IEEE Transactions on Industrial Electronics*, 62(12), pp.7762–7773.

Nielsen, J.S., 2013. *Risk-Based Operation and Maintenance of Offshore Wind Turbines*. Aalborg University.

Nielsen, J.S. & Sørensen, J.D., 2017. Bayesian Estimation of Remaining Useful Life for Wind Turbine Blades. *Energ*, 10(664).

Nielsen, J.S. & Sørensen, J.D., 2014. Methods for Risk-Based Planning of O&M of Wind Turbines. *Energies*, 7, pp.6645–6664.

Novaes, G. De et al., 2018. Prognostic techniques applied to maintenance of wind turbines: a concise and specific review. *Renewable and Sustainable Energy Reviews*, 81, pp.1917–1925.

Rasekhi Nejad, A. et al., 2014. A prognostic method for fault detection in wind turbine drivetrains. *Engineering Failure Analysis*, 42, pp.324–336. Available at: http://dx.doi.org/10.1016/j.engfailanal.2014.04.031.

Schwabacher, M. & Goebel, K., 2007. A Survey of Artificial Intelligence for Prognostics. In *AIAA Fall Symposium*. Arlington, Virginia: AIAA, pp. 107–114.

Si, X. et al., 2011. Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research*, 213(1), pp.1–14. Available at: http://dx.doi.org/10.1016/j.ejor.2010.11.018.

Sikorska, J. & Ma, L., 2011. Prognostic modeling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, 25, pp.1803–1836.

Sørensen, J.D., 2009. *Framework for Risk-based Planning of Operation and Maintenance for Offshore Wind Turbines*.

Tardieu, P., Nghiem, A. & Pineda, I., 2017. *Wind energy in*

Europe: Scenarios for 2030, Brussels.

Technical Committee CEN 319, 2010. *EN 13306 Maintenance Terminology*, Brussels.

Welte, T.M. & Wang, K., 2014. Models for lifetime estimation: an overview with focus on applications to wind turbines. *Advances in Manufacturing*, 2(1), pp.79–87.

BIOGRAPHIES

M. Asgarpour is a Mechanical Engineer specialized in performance monitoring and reliability assessment of wind turbines. He is currently leading the analytics and asset integrity management team in Vattenfall Wind. In parallel to his work, he is also an industrial doctoral research fellow at Civil Engineering Department of Aalborg University in Denmark focused on Bayesian risk and reliability based O&M planning of offshore wind farms.

J.D. Sørensen is professor at Department of Civil Engineering, Aalborg University in Denmark, and is noted for his research on structural reliability and wind energy systems.