



Norwegian University of
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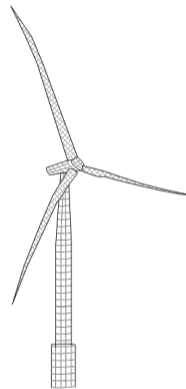
DIGITAL SOLUTIONS FOR OPERATION AND MAINTENANCE OF OFFSHORE WIND FARMS

Jørn Vatn/January-2024

Digital twins



Digital twins



Blade failure



Key questions

- ▶ What is a failure?
- ▶ How to prevent failures?
- ▶ How to represent a failure in a digital twin
- ▶ Is it only one digital twin, or are there several digital twins that communicate?

More about digital twins

- ▶ A Digital Twin (DT) in the current context is aimed as a *virtual representation* of a technical system, a production plant etc.
- ▶ Key elements of a DT are bigdata, artificial intelligence and simulations for real-time prediction, monitoring, control and optimization
- ▶ The DNV-RP-A204 Qualification and assurance of digital twins classifies the level of capability of a digital twin on a scale from 0-5 (0-stand-alone, 1-descriptive, 2-diagnostic, 3-predictive, 4-prescriptive, 5-autonomy)
- ▶ An objective of this lecture is to give some ideas related to level 3 and 4 on the DNV ladder

DNV-RP-A204



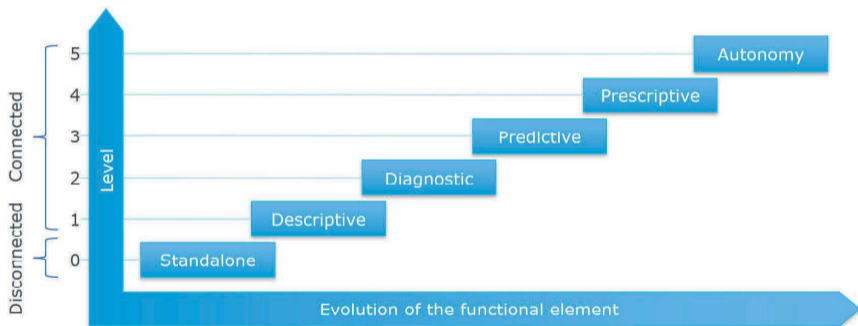
RECOMMENDED PRACTICE

DNV-RP-A204

Edition October 2020
Amended September 2021

Qualification and assurance of digital twins

DNV-RP-A204 - Evolution stages or capability of a functional element



Objectives of HAV6003

- ▶ Introduction to basic maintenance modelling and optimization
- ▶ Present some simple operation models, i.e., related to "Wind turbine/farm control" (HAV6002)
- ▶ Introduce relevant digital twins (maintenance, cost/prices, operations, weather)
- ▶ Program some "Sand-box" digital twins in Python
- ▶ Understand the value of digital twins that can provide real-time decision support relevant of maintenance and operation

What is a failure?

- ▶ Items are designed to perform one or more *functions*
- ▶ A failure is the termination of the ability to perform one or more of the required functions

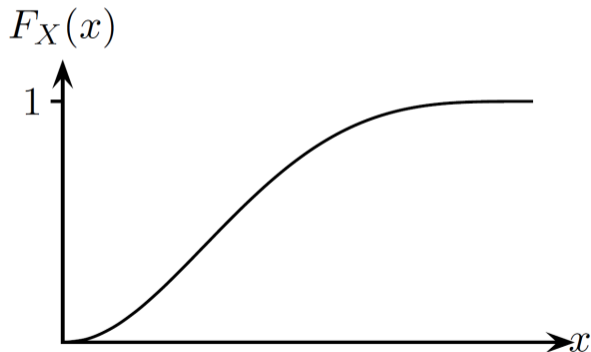
Probability theory

- ▶ Failures occur randomly
- ▶ Probability theory is the theory to describe the random nature of failures
- ▶ Probability density, distribution function and failure rate function are important terms

Cumulative distribution function

A stochastic variable X is characterized by its *cumulative distribution function* (CDF)

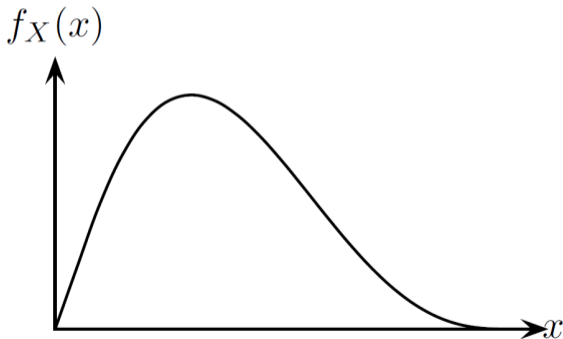
$$F_X(x) = \Pr(X \leq x)$$



Probability density function

For a continuous stochastic variable, the *probability density function* (PDF) is given by

$$f_X(x) = \frac{d}{dx} F_X(x)$$



Expectation

The expectation (mean) of X is given by

$$E(X) = \begin{cases} \int_{-\infty}^{\infty} x \cdot f_X(x) dx & \text{if } X \text{ is continuous} \\ \sum_j x_j \cdot p(x_j) & \text{if } X \text{ is discrete} \end{cases}$$

- ▶ The expectation can be interpreted as the long time run average of X , if an infinite amount of observations are available

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- ▶ The expectation can be interpreted as the long time run average of X , if an infinite amount of observations are available
- ▶ If X is representing time-to-failure, then $E(X) = \text{MTTF} = \text{Mean Time To Failure}$

Variance and standard deviation

The variance of a random quantity expresses the variation in the value X will take in the long run:

$$\text{Var}(X) = \begin{cases} \int_{-\infty}^{\infty} [x - E(X)]^2 \cdot f_X(x) dx & \text{if } X \text{ is continuous} \\ \sum_j [(x_j - E(X))]^2 \cdot p(x_j) & \text{if } X \text{ is discrete} \end{cases}$$

The standard deviation of X is given by

$$\text{SD}(X) = +\sqrt{\text{Var}(X)}$$

Failure rate function

- ▶ The failure rate function expresses the conditional probability that an item that has been functioning since it was put into function fails in a small time interval. The notation $z(t)$ is used to express the failure rate function
- ▶ The failure rate function may be expressed by:

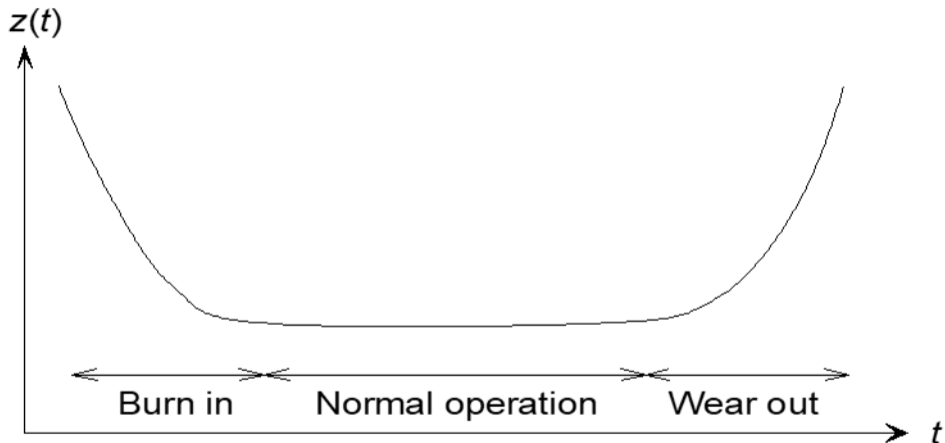
$$z(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t | t > T)}{\Delta t} = \frac{f(t)}{1 - F(t)} \quad (1)$$

- ▶ or rewritten as:

$$z(t)\Delta t \approx \Pr(t \leq T < t + \Delta t | t > T) \quad (2)$$

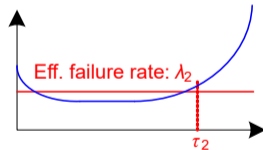
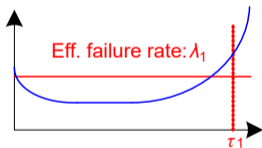
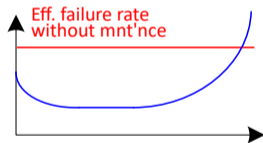
- ▶ which means that the failure rate function multiplied by the length of a small time interval, $[t, t + \Delta t]$, is approximately the probability that the item fails in the interval given that it is still functioning at the beginning of the interval, i.e., at time t .

Failure rate function (bath tub curve)



Effective failure rate

- ▶ By replacing the item with a new one at some interval τ , we may reduce the *effective failure rate*, $\lambda_E(\tau)$
- ▶ $\lambda_E(\tau)$ = expected # of failures per unit time with maintenance
- ▶ Examples with
 - ▶ No maintenance
 - ▶ Long maintenance interval, τ_1
 - ▶ Shorter maintenance interval, τ_2



Maintenance

- ▶ The combination of all technical and management actions during the life cycle of an item intended to retain the item in, or restore it to, a state in which it can perform as required
- ▶ Maintenance is important to achieve a high availability. In general availability depends on the following factors:
 1. Inherent reliability (e.g., quality, type of material used and design principles)
 2. Maintainability (how easy it is to perform maintenance)
 3. Maintenance support (resources, spare parts etc)

Maintenance Categories

The maintenance is often categorized into:

1. Corrective maintenance (CM), i.e., tasks performed as a result of a detected item failure or fault, to restore the item to a specific condition. CM tasks may be carried out *immediately* or be *deferred*.
2. Preventive maintenance (PM), i.e., planned maintenance tasks performed prior to failures. The activities are carried out in order to reduce the probability of failure, or increase the mean time to failure (MTTF). Types of PM tasks:
 - 2.1 Age-based
 - 2.2 Clock-based (calendar based)
 - 2.3 Condition-based
 - 2.4 Opportunity-based
 - 2.5 Overhaul, e.g., as part of a turnaround
3. Predictive maintenance, i.e., maintenance based on *prognoses* for the degradation of the item.

Preventive Maintenance Policies

- ▶ A preventive maintenance policy is a strategy that aims at minimizing the long run cost
- ▶ A policy both deals with qualitative issues like replace an item periodically at a given age, and quantitative issues like what age that should be
- ▶ The classical maintenance policies were basically considering age or calendar time as the decision variable to use in the optimization
- ▶ In light of “predictive maintenance” the condition of an item and future operational loads are becoming more important in order to minimize long run cost
- ▶ The need for “digital twins”

Terminology and Cost Function

- ▶ *Maintenance task*: A specific task to maintain an item determined by “what, where, how and when”. A task is part of the task space, \mathcal{A} , i.e.,
 $\mathcal{A} = a_1, a_2, a_3, \dots$
- ▶ *Maintenance decision*: A process δ to select a specific maintenance task $a_i \in \mathcal{A}$. δ depends on available data \mathcal{D} , cost, operating conditions etc.
- ▶ *Maintenance strategy*: An overall framework describing how the maintenance decision problem shall be approached. A strategy embraces an objective function, often denoted the cost function:

$$C = C(\mathbf{a}, \delta, t, \mathcal{D}, \mathcal{D}_{OC}, t_{cal}, \dots)$$

Terminology and Cost Function, cont

- ▶ $C = C(a, \delta, t, \mathcal{D}, \mathcal{D}_{OC}, t_{cal}, \dots)$
- ▶ In addition to a and \mathcal{D} the cost function depends on the time t of executing the maintenance, the operational context \mathcal{D}_{OC} , the calendar time t_{cal}, \dots (e.g., inside / outside working hours) and so on
- ▶ Maintenance optimization = minimize long run cost, e.g., cost per unit time:

$$C(\tau) = \frac{E[\text{cost in a cycle}]}{E[\text{length of cycle}]}$$

Effective failure rate, cont.

- ▶ To optimize maintenance we need the effective failure rate
- ▶ Obtaining the effective failure rate is not easy, but as a first approximation we may use:
 - ▶ Low ageing: $\lambda_E(\tau) = 0.79\tau/\text{MTTF}^2$
 - ▶ Medium ageing: $\lambda_E(\tau) = 0.71\tau^2/\text{MTTF}^3$
 - ▶ Strong ageing: $\lambda_E(\tau) = 0.67\tau^3/\text{MTTF}^4$
- ▶ where MTTF = Mean Time To Failure *without* any maintenance
- ▶ Low ageing means a rather undefined start of the right part of the bath tub curve, e.g., due to many different failure mechanisms, less mechanisms gives stronger ageing

Expected cost per unit time

$$C(\tau) = c_{PM}/\tau + \lambda_E(\tau) [c_{CM} + c_{EP} + c_{ES}]$$

where

- ▶ c_{PM} is the cost of a preventive maintenance action
- ▶ $\lambda_E(\tau)$ is the *effective failure rate*, i.e., the expected number of failures per time unit when the component is preventively maintained every τ time unit
- ▶ c_{CM} is the cost of a corrective maintenance (CM) action
- ▶ c_{EP} is the expected production losses upon a component failure
- ▶ c_{ES} is the expected safety cost upon a component failure, including material damages and environmental losses
- ▶ In the following we let $c_U = [c_{CM} + c_{EP} + c_{ES}]$

Exercise - Exam 2023 - Yaw motor

- ▶ 10 MW turbine, average effect = 6 MW
- ▶ Energy price = 0.5 NOKs per kwh
- ▶ Reliability and cost figures
 - ▶ MTTF = 5 years if not replaced
 - ▶ Strong ageing
 - ▶ $c_{PM} = 15\ 000$ NOKs
 - ▶ $c_{CM} = 30\ 000$ NOKs
 - ▶ MDT = 12 hours

▶ Show solution in Excel



Optimal value of τ

- ▶ In order to derive an optimal maintenance interval we introduce a more general formula for the effective failure rate:

$$\lambda_E(\tau) = \left(\frac{\Gamma(1 + 1/\alpha)}{\text{MTTF}} \right)^\alpha \tau^{\alpha-1}$$

- ▶ Where the ageing parameter α is obtained by:
 - ▶ Low ageing: $\alpha = 2$
 - ▶ Medium ageing: $\alpha = 3$
 - ▶ Strong ageing: $\alpha = 4$
- ▶ $\Gamma()$ is the gamma function (e.g., =Gamma(1+1/4) in Excel)

Optimal value of τ

Parameters used in the optimization

- ▶ $MTTF = 5$ years
- ▶ $MDT = 12$ hours
- ▶ $\alpha = 4$
- ▶ $c_{PM} = 15\,000$ NOKs
- ▶ $c_{CM} = 30\,000$ NOKs
- ▶ $c_{EP} = MDT \cdot 0.5 \cdot 6\,000 = 36\,000$ NOKs
- ▶ $c_U = c_{CM} + c_{EP} = 66\,000$ NOKs

Optimal value of τ

By equating the derivative of the cost equation (objective function) to zero, we find the optimal interval:

$$C(\tau) = c_{PM}/\tau + \lambda_E(\tau)c_U$$

$$C(\tau) = c_{PM}/\tau + \left(\frac{\Gamma(1 + 1/\alpha)}{MTTF}\right)^\alpha \tau^{\alpha-1} c_U$$

$$C'(\tau) = -c_{PM}/\tau^2 + \left(\frac{\Gamma(1 + 1/\alpha)}{MTTF}\right)^\alpha (\alpha - 1)\tau^{\alpha-2} c_U = 0 \implies$$

$$\tau^* = \frac{MTTF}{\Gamma(1 + 1/\alpha)} \left(\frac{c_{PM}}{c_U(\alpha - 1)}\right)^{1/\alpha}$$

Optimal value of τ

$$\tau^* = \frac{\text{MTTF}}{\Gamma(1 + 1/\alpha)} \left(\frac{c_{\text{PM}}}{c_{\text{U}}(\alpha - 1)} \right)^{1/\alpha} = \frac{4}{\Gamma(1 + 1/3)} \left(\frac{15\,000}{66\,000 \cdot 3} \right)^{1/4} \approx 2.2 \text{ years}$$

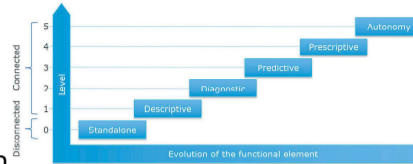
Alternatively, we could solve the problem by a minimization routine, for example by the Solver in Excel. The cost function to minimize is:

$$C(\tau) = c_{\text{PM}}/\tau + \lambda_{\text{E}}(\tau)c_{\text{U}}$$

► Show solution in Excel

Digital twin

- ▶ The Excel model from the exercise *is* a digital twin
- ▶ A specific failure is not a part of the digital twin
- ▶ A failure in the digital twin is represented by the effective failure rate $\lambda_E(\tau)$, i.e., a *probabilistic digital twin*
- ▶ The digital twin has “What-if” capabilities, i.e., we can investigate what will happen with longer maintenance interval
- ▶ The digital twin has no “Real-time” updating capabilities, i.e., it is a *stand-alone* digital twin, i.e., level 0 in the DNV-ladder



Exercise - Revisited - Real-time connected DT

- ▶ The 10 MW turbine is in average producing 6 MW
- ▶ What happens in periods of time when average production is 8 MW?
- ▶ In bad weather, MDT might be increased to 24 hours
- ▶ etc
 - ▶ $MTTF = 5$ years
 - ▶ $c_{PM} = 15\ 000$ NOKs
 - ▶ $c_{CM} = 30\ 000$ NOKs
 - ▶ $MW = ?$ - Depends on weather
 - ▶ $MDT = ?$ - Depends on weather

▶ Show solution in Excel

Predictive maintenance - PdM

- ▶ In contrast to traditional calendar based preventive maintenance the main idea of a predictive maintenance strategy is to utilize component condition, future loads, and opportunity windows to determine a “just in time” plan for maintenance
- ▶ Condition information is basically used for:
 1. Anomaly detection, i.e., early warning of coming events (Level 2)
 2. Diagnostics, i.e., the search for root causes behind symptoms observed (Level 2)
 3. Prognostics, i.e., estimation of degradation rate, time to failure, remaining useful life etc. based on relevant information (Level 3)
- ▶ In this following we only focus on prognostics (Level 3) and decision making (Level 4, i.e., prescriptive)

Predictive maintenance - PdM

- ▶ The mathematical modelling framework is more demanding for PdM compared to the example
- ▶ Some key elements
 - ▶ What are the health indicators to predict future failures?
 - ▶ What are the models to describe the stochastic behaviour of the health indicators
 - ▶ What are influencing factors affecting the health indicators (i.e., loads)
 - ▶ RUL = Remaining Useful Lifetime
- ▶ Today, we will present one model, some more models will be presented in HAV6003...

Brownian motion and the Wiener process

Brownian motion is the random motion of particles in a fluid where collisions between particles result in a rather chaotic behaviour. Brownian motion is described by a continuous-time stochastic process named the Wiener process, i.e., $\{W(t), t \in \Theta\}$ is characterized by:

- ▶ $W(0) = 0$
- ▶ $\{W(t)\}$ is almost surely continuous
- ▶ $\{W(t)\}$ has independent increments
- ▶ $W(t) - W(s) \sim \mathcal{N}(0, t - s)$ (for $0 \leq s \leq t$)

where $\mathcal{N}(\mu, \sigma^2)$ denotes the normal distribution with expected value μ and variance σ^2

Wiener process

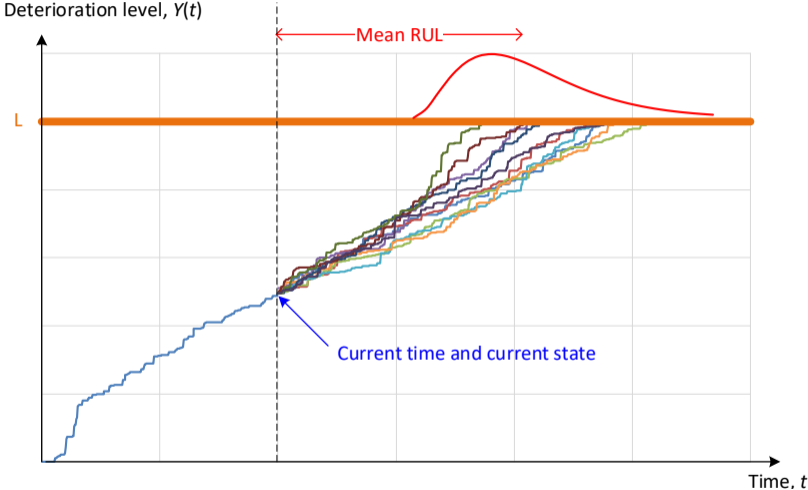
The Wiener process defined above is fluctuating around zero. A related stochastic process is defined by:

$$Y(t) = \mu t + \sigma W(t)$$

This process is called a Wiener process with drift μ and infinitesimal variance σ^2 . For the Wiener process with drift we have:

$$Y(t) - Y(s) \sim \mathcal{N}(\mu(t - s), \sigma^2(t - s))$$

Wiener process and time to failure



Wiener process and time to failure

- ▶ Let $\{Y(t)\}$ be a stochastic process describing the degradation of a component
- ▶ Assume the component will fail the first time $Y(t) > L$
- ▶ Let T be the time to failure for the component
- ▶ It may be shown that the time to failure, i.e., the time to the first passage of the limit L is inverse-Gauss distributed:

Wiener process and time to failure

$$F_T(t) = \Phi\left(\frac{\sqrt{\lambda}}{\nu}\sqrt{t} - \sqrt{\lambda}\frac{1}{\sqrt{t}}\right) + \Phi\left(-\frac{\sqrt{\lambda}}{\nu}\sqrt{t} - \sqrt{\lambda}\frac{1}{\sqrt{t}}\right) e^{2\lambda/\nu}$$

and

$$E(T) = \nu$$

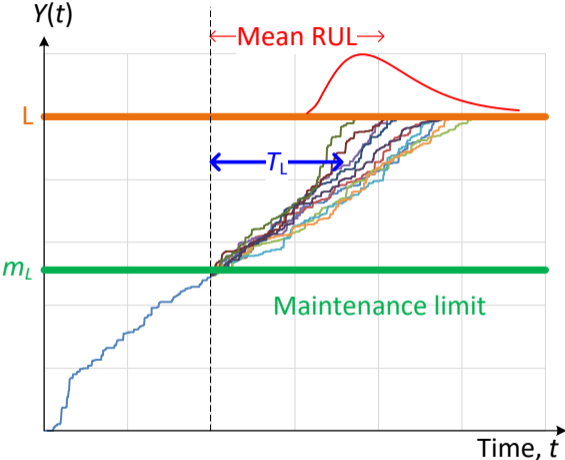
$$\text{Var}(T) = \nu^3/\lambda$$

where $\nu = L/\mu$ and $\lambda = L^2/\sigma^2$. In terms of the original parameters we have $E(T) = L/\mu$ and $\text{Var}(T) = L\sigma^2/\mu^3$.

Wiener process and maintenance cost digital twin

- ▶ Assume that we can observe the degradation process continuously
- ▶ When degradation *approaches* the failure limit, L , we will place a request to replace the component with a new component
- ▶ We assume that there is a deterministic lead time, say T_L
- ▶ The objective is to determine the maintenance limit, m_L , i.e., how close to the failure limit we dear to go

Wiener process with maintenance and failure limit



Wiener process and maintenance cost digital twin

The cost equation to minimize is:

$$C(m_L) = \frac{C_R + C_F F(T_L | m_L) + C_U \int_0^{T_L} f(t | m_L) (T_L - t) dt}{MTBR(m_L)}$$

where

- ▶ C_R = cost of renewal/replacement
- ▶ $C_F = C_{CM} + C_T$ = cost of failure (additional cost for corrective maintenance (CM) and cost for the failure event (T=Trip))
- ▶ C_U = cost per hour down time
- ▶ $F()$ and $f()$ are CDF and PDF for remaining life time given maintenance limit m
- ▶ $MTBR(m_L)$ = Mean Time Between Renewals

▶ Show in Excel (Average)

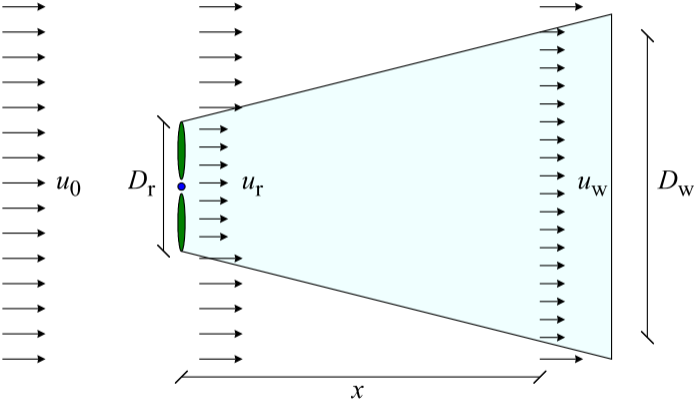
Relax cost

- ▶ When we reach the maintenance limit we could relax on production, e.g.:
 - ▶ Produce less items
 - ▶ Yawing of front runner turbines
- ▶ Let x be a measure of how much we relax on production, i.e., a decision variable
- ▶ Let $c_{Rx}(x)$ be corresponding production loss per unit time
- ▶ The cost equation to minimize now is:

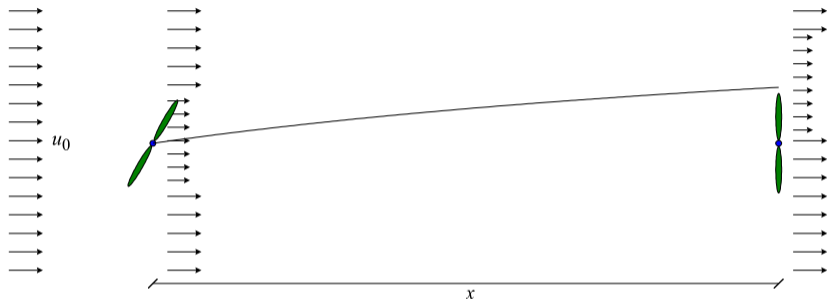
$$C(m_L, x) = \frac{c_R + c_F F(T_L | m_L, x) + c_U \int_0^{T_L} f(t | m_L, x) (T_L - t) dt + c_{Rx}(x) T_L}{MTBR(m_L)}$$

where $F()$ and $f()$ now depends on x as well as the maintenance limit

Wake modelling



Wake centreline with yawing

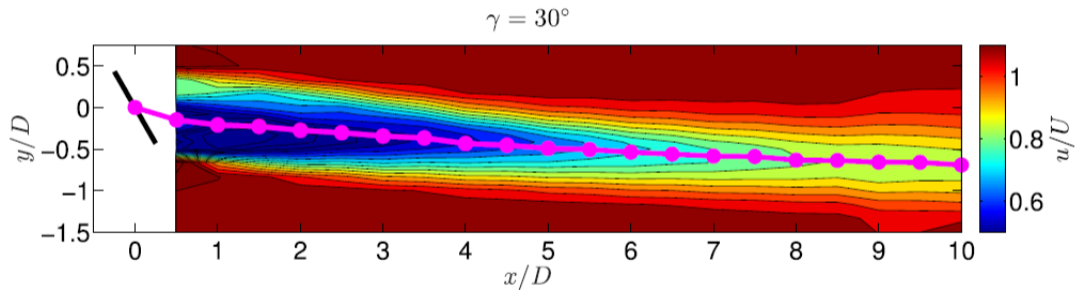


$$y_C(x, \gamma) = 1.25 D_r \frac{\cos^2(\gamma) \sin(\gamma) C_T(a, \gamma)}{2\beta} \left(1 - \frac{D_r}{\beta x + D_r} \right)$$

Wake wind speed impact

11-8 Howland *et al.*

J. Renewable Sustainable Energy **8**, 043301 (2016)



Relax modelling - Offshore wind

- ▶ In general, several turbines could “relax”
- ▶ In light of “wake effects”, it is of particular interest to consider relaxing on the “front runners”
- ▶ Two aspects need to be considered:
 - ▶ The impact of the relax on the degradation rate
 - ▶ The impact on direct profit, i.e., both the front runners and downstream turbines

Wake modelling, continued

- ▶ First of all we should acknowledge that engineering models are not very accurate, and in particular to consider the situation at the wind farm level, such a model might be too simple
- ▶ To optimize production, independent of the impact of degradation, yawing could impact the loss in inn speed
- ▶ We do not propose models here, but yawing means reduced swiping area of the frontrunner turbine, and a reduction factor for the front runner could be something like $\cos\phi$, where ϕ is the yawing angle
- ▶ However, the total impact on the effect this will have on the downstream wake profile is not that easy to model, and far beyond the scope of this presentation

Wake modelling, continued

- ▶ From the maintenance perspective, the turbulence is our main concern wrt the wake effect
- ▶ In the wake shadow, it is expected to be much turbulence. We could may be use something like the inverse speed reduction factor as a starting point for an “increase” factor of e.g., fatigue loads
- ▶ Note the difference:
 - ▶ General increased load due to turbulence, and how we consider this as a part of the overall objective function for wind farm control
 - ▶ The explicit modelling of a given situation, where we have observed a critical degradation, and the aim is to reduce the risk of failure until maintenance could be carried out, i.e., our example

Thank you for your attention

