Lifespan impact of curtailment scenarios

D1.2



WaterstofNet

Francisco de Nolasco
26 Juni 2026

1 Table of contents

1 Table of contents 1
2 Introduction 2
3 Data-driven lifetime consumption analysis 3
3.1 Impact of downtime on structural loads 3
3.2 Data-driven fleetwide fatigue rate estimation 4
3.3 Fatigue consumption calculation given downtime 5
4 Conclusions 10
5 Bibliography 11

2 Introduction

Among the several reasons why offshore wind turbines might experience downtime, grid-related curtailment has seen an increase in recent years. Besides ensuring grid stability, turbines might be curtailed due to mismatches between electricity supply and demand, wherein supply exceeds demand and energy prices become negative. This means that, in such an event, produced energy comes to waste due to market pricing. In the context of Hyacint, research is being conducted on how this lost energy can still be utilized via hydrogen production, using offshore electrolysis platforms.
However, it has been observed that for certain types of turbines/foundations – particularly more recent, bigger models – downtime accelerates fatigue life consumption [1]. As such, it is crucial to accurately understand the impact of curtailments, both on the energy production of wind farms, but also on the structural life of the foundations, as these represent deviations from design. On the one hand, they can represent an operational risk, but also jeopardize lifetime extensions. This is essential to ensure the technical and economic feasibility of proposed hydrogen systems.
The current deliverable contributes to T1.4. "Data driven assessment of lifetime consumption", where the impact on lifetime consumption will be determined based on structural health monitoring (SHM) data collected from real-world monitoring systems and the historical scenarios for the expected downtime periods and the associated time patterns of curtailments for the period 2020-2025. In this context, D1.2 benefits from T1.1. and T1.3.

On the one hand, T1.1. provides an analysis that attempts to quantify the near-future potential based on historical curtailment scenarios for the period 2020-2025 in the Belgian North sea. It examines both overloading of the transmission network and negative electricity prices as sources for downtime. This will inform the current deliverable in the types of curtailment scenarios for which lifetime ought to be estimated.

On the other hand, T1.3. determines the intensity, the frequency and duration of the downtime scenarios. These factors play a key role on the impact of lifetime consumption, as the load degree to which wind turbines are curtailed can lead to vastly different structural loads, particularly when accounting for the transient component.

The results described in this deliverable constitute a necessary input for the cost model to calculate the economic value of the downtime scenarios of curtailment scenarios of task 1.5 of the Hyacint project.

3 Data-driven lifetime consumption analysis

3.1 Impact of downtime on structural loads

In Belgium, wind farms are increasingly tapping into flexibility markets, which offer financial incentives to modulate power production based on grid demand. During periods of high wind generation but low consumption, it is often more economically advantageous to intentionally reduce a wind farm's output (curtailment) rather than running at maximum capacity.

For hybrid wind-hydrogen systems, this flexibility allows operators to dynamically redirect excess electricity toward hydrogen production or scale it back based on real-time market signals.

However, operationally driven downtime has an impact on the structural loads experienced by the offshore wind turbine's foundation. The cyclical loads which support structures incur due to operation and the environment will induce some stresses into the material (steel) and contribute to its mechanical fatigue. The fatigue of the primary steel – *i.e.*, from the foundation – is a key design driver. That is to say, when designing and dimensioning a turbine and its support structure, the focus will be on dynamics rather than bearing capacity (ultimate limit strength). As such, design assumes that fatigue accumulate over a turbine's lifetime until a threshold (where fatigue damage = 1), upon which the design life has been reached (usually somewhere between 20 and 30 years).

During design, several factors are taken into account when calculating the fatigue life (*e.g.*, the probability distribution of wind speeds, the forecasted amount of maintenance time, etc.). Importantly, market-driven downtime (curtailment) is not accounted for during design, as forecasting future long-term electricity pricing isn't feasible. As such, curtailment can be, from the point-of-view of structural fatigue life, problematic, as it is not accounted in the design assumptions. Specifically for newer farms, this has an added saliency as design codes have been optimized and structural reserves have diminished.

Curtailments introduce structural loads. These loads are forces applied to structures which lead to displacements. When wind pushes against a structure, the latter bends. This may cause potential damage to the structure if continuously repeated. There are two types of structural loads during curtailments:

- **Transient loads**: Big, quasi-discrete loads which occur because the aerodynamic force loading the rotor is (partially) released when a new power set-point has to be rapidly reached. It is always more damaging than normal operation.

- **Steady-state loads**: Loads incurred during curtailment, after the transition between rated and curtailed states has led to a steady-state. They can be both beneficial or prejudicial, depending on the turbine type, dynamics, wind speed and sea state.

Therefore, any strategy predicated upon the leveraging of curtailments needs to be carefully assessed, as not to jeopardize the asset's lifetime. In this document, we will focus on the steady-state loads. We purposefully do not include transient loads, as these are more complex to characterize: one must not only know the number of hours under curtailment, but also the number of curtailment actions and, furthermore, the starting and ending set-points (curtailing from 100% to 50% is different than from 80% to 20%). A transient matrix could be generated, but due to this increased complexity and sparsity it would lead to mostly empty bins.

Within this context, the VUB (Vrije Universiteit Brussel), has developed a data-driven fatigue rate matrix given different curtailment rates and a methodology to account for the impact of downtime on the total fatigue.

3.2 Data-driven fleetwide fatigue rate estimation

The fatigue rate matrix developed in this deliverable is based on a key metric known as Damage Equivalent Loads (DEL). Conceptually, DELs translate a highly variable, dynamic strain signal—which a structure experiences over time—into a single, constant amplitude load. This single representative load would produce the exact same amount of structural fatigue damage as the actual, complex loading history. As such, they encapsulate the fatigue rate experienced by a given structure and are widely adopted by load engineers. This rate can then be compared with the rate established during design in order to enable any decision regarding the lifetime (e.g., extension).

Without entering in greater theory (which can be consulted in [2]), it suffices to say that, practically, DELs are estimated for every 10-mins for every turbine with an installed strain gauge. Strain gauges provide strain measurements which enable the calculation of the bending moments experienced at the interface between the tower and transition piece (which connects with the foundation). The bending moments are usually decoupled into the normal (fore-aft) and lateral (side-to-side) directions, with relation to the incoming wind/nacelle orientation. So, by rain flow counting the stress cycles (n_i), the DEL is expressed as:

$$DEL = \left(\frac{\sum_{i=1}^{n} n_i \cdot \Delta S_i^m}{N_{eq}}\right)^{1/m} \quad (1)$$

With m, the S-N (stress-number of cycles) curve's Wöhler exponent (here 5), N_{eq}, the reference number of equivalent cycles, here 10^7 and ΔS_i the load/stress amplitude for bin I (from the rainflow counting).

DELs, besides being used during design to indicate permissible fatigue rates, allow the comparison between fatigue rates of different periods and operations by recasting everything back into the same framework. This is done through the weighted m-powered summation:

$$DEL_{total} = \sqrt[m]{\sum_{i=1}^{n} P_{occ,i} \cdot {DEL_i}^m} \quad (2)$$

Where $P_{occ,i}$ is the probability of occurrence of bin i. Here, i could represent, *e.g.*, each operational case.

In this deliverable, we will employ the DELs estimated by a data-driven model taking acceleration and SCADA[1] parameters as inputs, as described in [2]. The advantage of using this model, instead of relying solely on measured DELs (through the strain gauge-installed turbines [5]), is that it allows to encompass more a greater number of wind speed bins, as more environmental conditions are seen farm-wide for the different power set-points.

3.3 Fatigue consumption calculation given downtime

As described in the previous section, we use the DEL estimates farm-wide to establish the fatigue consumption matrix based on the power set point (100%, 80%, etc. of the rated power) and wind speed bins between 0-24 m/s with 0.5 m/s increments. So, given a wind speed – power set point bin with i 10-minute DEL elements, the total bin DEL will be

$$DEL_{bin} = \sqrt[m]{\frac{1}{n}\sum_{i=1}^{n} {DEL_i}^m} \quad (3)$$

Which is a special case of Eq. (2), where the probability of occurrence of each individual DEL is the same (all DELs are 10-min).
This is visualised in Figure 1. The cells with a red border present the actual data, whereas other cells (for which there is no data for that bin) were interpolated (in between two existing cells), or backwards filled. It is noticeable that missing cells occur for lower wind speeds, especially for higher power set points, which generally are only achieved after the cut-in speed (5 m/s).

[1] Supervisory Control And Data Acquisition

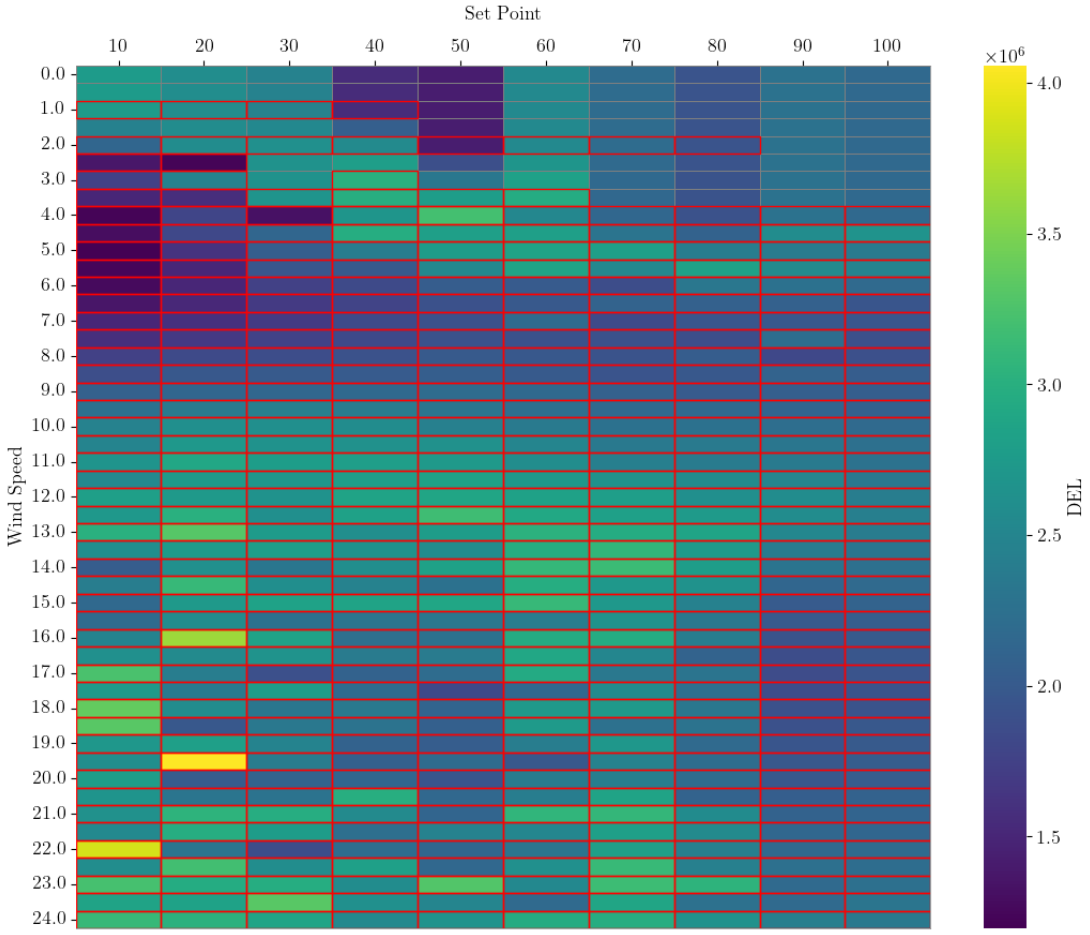

Figure 1. Data-driven DEL matrix based on wind speed [m/s] and power set point relative to rated power [-]. Red cells, data-based bins. Other cells, interpolated.

This table is translated into Excel, which can be seen in Figure 2

Absoluut DEL [Nm] - Stationary										
Park set-point [% van maximaal vermogen]	10	20	30	40	50	60	70	80	90	100
Vrije windsnelheid [m/s]										
0.5	2.756.446	2.588.775	2.453.391	1.542.956	1.426.772	2.547.636	2.192.502	1.940.884	2.276.854	2.163.811
1.0	2.756.446	2.588.775	2.453.391	1.542.956	1.426.772	2.547.636	2.192.502	1.940.884	2.276.854	2.163.811
1.5	2.440.616	2.579.923	2.536.517	2.049.330	1.426.772	2.547.636	2.192.502	1.940.884	2.276.854	2.163.811
2.0	2.124.787	2.571.072	2.619.643	2.555.704	1.426.772	2.547.636	2.192.502	1.940.884	2.276.854	2.163.811
2.5	1.366.247	1.227.196	2.637.749	2.785.463	1.877.319	2.685.010	2.178.169	1.936.116	2.276.854	2.163.811
3.0	1.753.111	2.453.923	2.655.855	3.015.222	2.327.865	2.822.384	2.163.836	1.931.348	2.276.854	2.163.811
3.5	1.507.555	1.566.101	2.673.961	2.988.937	2.778.412	2.959.758	2.149.503	1.926.581	2.276.854	2.163.811
4.0	1.222.164	1.780.161	1.325.815	2.684.999	3.198.108	2.524.291	2.135.170	1.921.813	2.276.854	2.163.811
4.5	1.293.158	1.813.607	2.129.327	2.967.398	2.805.242	2.796.844	2.302.044	2.087.149	2.572.240	2.661.554
5.0	1.195.264	1.616.329	2.043.903	2.397.543	2.769.569	2.855.315	2.804.975	2.398.876	2.371.407	2.363.074
5.5	1.232.509	1.499.382	1.965.498	1.987.275	2.526.935	2.854.542	2.536.446	2.833.614	2.548.155	2.473.893
6.0	1.266.273	1.502.010	1.745.391	1.840.332	2.031.930	2.007.587	1.862.613	2.333.478	2.259.272	2.173.037
6.5	1.361.078	1.514.852	1.684.669	1.773.916	1.905.840	1.986.386	2.099.536	2.075.324	2.076.159	1.953.903
7.0	1.500.502	1.594.995	1.686.964	1.835.941	1.906.369	2.187.870	1.837.045	1.962.060	1.974.866	1.957.504
7.5	1.584.659	1.669.149	1.765.157	1.823.264	1.916.271	1.909.343	1.909.173	1.871.329	2.209.104	1.888.645
8.0	1.751.578	1.843.457	1.856.464	1.913.496	1.993.858	1.971.110	1.930.089	2.025.495	1.814.157	1.892.608
8.5	1.876.956	1.969.164	1.999.022	2.007.160	2.040.719	1.997.513	1.937.826	1.970.216	2.090.409	2.032.347
9.0	2.077.637	2.133.973	2.137.937	2.162.121	2.196.625	2.161.028	2.074.105	2.005.830	2.054.086	2.040.555
9.5	2.262.089	2.368.926	2.422.937	2.369.297	2.312.926	2.228.386	2.167.859	2.164.915	2.103.334	2.059.110
10.0	2.466.294	2.609.176	2.610.677	2.575.959	2.430.085	2.367.863	2.267.415	2.260.055	2.219.385	2.177.280
10.5	2.482.366	2.719.158	2.647.314	2.634.292	2.630.058	2.498.243	2.348.609	2.360.541	2.322.647	2.240.033
11.0	2.673.070	2.895.790	2.779.147	2.786.350	2.737.887	2.582.747	2.414.871	2.374.324	2.367.842	2.276.264
11.5	2.542.832	2.742.939	2.708.862	2.788.257	2.841.622	2.715.810	2.652.008	2.563.526	2.496.575	2.338.635
12.0	2.798.938	2.736.605	2.647.608	2.859.292	2.883.363	2.837.822	2.789.893	2.607.826	2.581.488	2.392.200
12.5	2.721.623	3.012.261	2.614.475	2.832.673	3.164.275	2.910.009	2.815.006	2.747.221	2.578.610	2.414.830
13.0	3.008.216	3.298.955	2.755.538	2.596.118	2.764.186	3.023.376	2.954.494	2.861.989	2.520.715	2.382.753
13.5	2.602.840	2.752.355	2.793.224	2.656.009	2.575.328	2.964.007	3.084.086	2.740.938	2.388.725	2.302.516
14.0	2.033.756	2.618.058	2.315.620	2.596.204	2.837.946	3.103.558	3.145.721	2.780.106	2.295.262	2.245.860
14.5	2.394.674	3.118.088	2.595.468	2.466.878	2.264.487	2.968.454	2.721.145	2.647.858	2.132.425	2.175.463

Figure 2. Excel table of DEL values per wind speed [m/s] and power set point [%] bins. A power set point of 100% means no curtailment.

We can then apply this to the table determining the number of curtailed hours. By knowing the total number of hours spent under curtailment, we can determine $P_{c,b}$, the probability of each individual curtailment bin (n_hours_bin/n_hours_total) and, as such, we can determine a DEL_c (c, curtailment) by employing Equation (2). This is the fatigue rate solely due to time spent in downtime, for all downtime cases combined, as seen in Eq. (4):

$$DEL_c = \sqrt[m]{\sum_{b=1}^{B} P_{c,b} \cdot {DEL_{c,b}}^m} \qquad (4)$$

There are several ways one can compare this value against expected or *'nominal'* operation. For example, we could focus on comparing the DEL of curtailment against what would have been

the expected (nominal) DEL *for the same wind conditions during the same period* (the curtailed hours). So, we just need to count the number of curtailed hours per wind speed bin, divide this by the total number of downtime hours and we get the probability of curtailment for each wind speed bin. Having the probabilities of occurrence, we can apply Eq. (2), but applying it solely to the 100% set point column (rated operation). This gives us what would be the rated (nominal) DEL_n for the times curtailment was occurring:

$$DEL_n = \sqrt[m]{\sum_{bw=1}^{BW} P_{ws,bw} \cdot {DEL_{100,bw}}^m} \quad (5)$$

Having both the nominal and curtailment DELs for the same number of hours, we can compare the fatigue load increase the curtailment represented with relation to nominal operation under the same wind conditions.

However, if we want to compare the impact over the entire 5-year period of the study, another nominal DEL value needs to be calculated. In this case, we again apply Eq. (5), but this time, the wind speed bin probabilities of occurrence ($P_{ws,bw}$) do not depend on the number of curtailed hours, but can be instead directly extracted from the Weibull distribution of wind speeds for the period (2020-2025). In this document, we present how this would be estimated based on the distribution of measured wind speeds for 1 year.

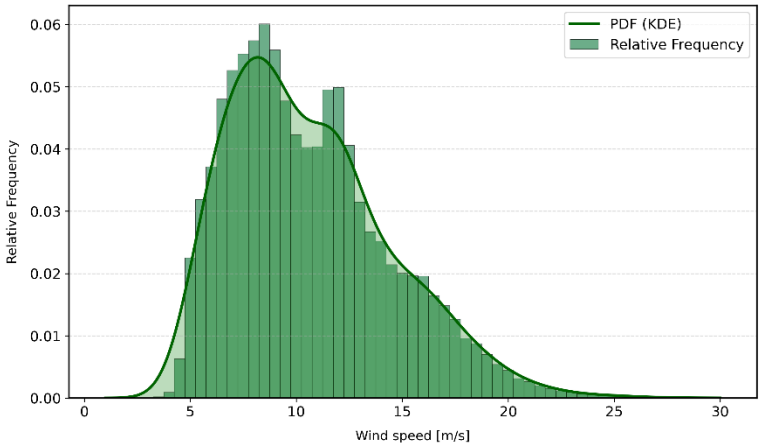

Figure 3. Wind speed distribution for 1 year of data (example).

Having both the nominal and curtailment DELs, if we want to estimate the impact of the curtailments over the entire period, we need to combine both, as in Equation (6):

$$DEL_{comb} = \sqrt[m]{P_c \cdot {DEL_c}^m + P_n \cdot {DEL_n}^m} \quad (6)$$

Where $P_c = {}^{n_c}/_{n_t}$ (number of curtailment hours/number of total hours in the period = 43.800) and $P_n = {}^{(n_t - n_c)}/_{n_t}$.

We can show some example results for a given curtailment matrix, totalling 681 downtime hours:

Nominal DEL (5 year)	Curtailment DEL = (Pcb1*DELcb1**m + ... + Pcbi*DELcbi**m)**(1/m)		Nominal DEL (for curtailed hours)
2167667,24	2338148	cb = curtailment bin	2191232,5
	Combined DEL = (Pc*DELc**m + Pn*DELn**m)**(1/m)		
	2170760	c = curtailment ; n = nominal	Increase (%) on curtailed hours
			6,7046784
	Increase (%) on 5 years		
	0,142679		

Figure 4. Increase of DEL over 5 years (%) and for the curtailment hours.

In this case, we estimate the nominal DEL as previously described (Eq. 4), by employing the 1-year wind distribution matrix to the DELs at rated power (100% set point).

The curtailment DEL is estimated according to Eq. (5), and combined with the nominal DEL as in Eq. (6). In this case, the probability of curtailment is $\frac{681}{43800}$ and the probability of normal operation $1 - \frac{681}{43800}$, where 681 is the number of hours of curtailment and 43800 the total number of hours of the last five years.
Having the combined DEL, we can then compare this against the nominal DEL which, in this case, leads to a 0.14% increase.

As mentioned above, this comparison can be done purely for the curtailment hours instead of the full period. In this case, the nominal DEL for the curtailed hours simply gets the probability of each wind speed bin based on the curtailment matrix and then directly compares this nominal value against the curtailment DEL. For this case, we can estimate that, during the curtailed hours, loads were 6.7% higher than nominal operation.

These values are taken as an example; the true value of the provided matrix comes to the fore in its ability to enable the testing of multiple curtailment scenarios and their impact on fatigue rates.

4 Conclusions

This deliverable establishes a data-driven framework within Task 1.4 to evaluate the long-term impact of operational curtailments on the fatigue life consumption of offshore wind turbine foundations in the Belgian North Sea. It pairs real-world Structural Health Monitoring (SHM) data with predictive downtime profiles for the 2020–2025 period, bridging power market flexibility and structural asset integrity.

While tapping into flexibility markets and redirecting surplus electricity to offshore hydrogen production could offer economic and grid-balancing benefits, market-driven downtime represents a distinct deviation from original structural design assumptions. Newer, larger turbine models operate with optimized design codes and tighter structural reserves, rendering them increasingly sensitive to accelerated fatigue when subjected to unplanned operational downtime.

The methodology decouples the dual nature of downtime stresses by breaking them down into **transient loads** (the highly damaging, discrete forces incurred during rapid power set-point transitions) and **steady-state loads** (the ongoing post-transition forces influenced by environmental conditions). In this document, only steady-state loads were taken into account, as the increased complexity of transient loads would lead to data sparsity in our calculations. The framework provides operators with two critical comparative pathways to assess structural degradation: (1) short-term operational impact and (2) long-term lifecycle impact. The former provides a direct comparison of curtailment fatigue against nominal (100% rated) operation under identical localized wind conditions. The latter allows for the integration of Weibull wind distributions to project overall fatigue accumulation over the entire 5-year macro-period (2020–2025).

Ultimately, this work enables operators and researchers to easily update the downtime matrix and investigate the impact different curtailment strategies might have on the fatigue rates (and, ultimate, fatigue life), of a given asset.

5 Bibliography

[1] K. Robbelein, P.-J. Daems, T. Verstraeten, N. Noppe, W. Weijtjens, J. Helsen en C. Devriendt, „Effect of curtailment scenarios on the loads and lifetime of offshore wind turbine generator support structures," *Journal of Physics: Conference Series,* vol. 2507, nr. 1, p. 012013, 2023.

[2] F. d. N. Santos, N. Noppe, W. Weijtjens en C. Devriendt, „Farm-wide interface fatigue loads estimation: A data-driven approach based on accelerometers," *Wind Energy,* vol. 27, nr. 4, pp. 321-340, 2024.

[3] N. FLORIS, „Version 3.4," 2023. [Online]. Available: https://github.com/NREL/floris. [Geopend 26 06 2024].

[4] D. van Binsbergen, P.-J. Daems, T. Verstraeten, A. R. Nejad en J. Helsen, „Hyperparameter tuning framework for calibrating analytical wake models using SCADA data of an offshore wind farm," *Wind Energ. Sci.,* pp. 1507-1526, 2024.

[5] International Electrotechnical Commission, *Wind energy generation systems - Part 12-1: Power performance measurement of electricity producing wind turbines (No. IEC 61400-12-1),* 2017.

WaterstofNet
Open Manufacturing Campus
Slachthuisstraat 112 bus 1
2300 Turnhout
België

T +32 (0)472 40 41 94

Kantoor Nederland

Automotive Campus
Automotive Campus 30
5708 JZ Helmond
Nederland

WaterstofNet
WaterstofNet

WaterstofNet

Waterstofnet.eu