IEA Wind Task 46

Erosion of wind turbine blades

Accuracy of LEE performance loss model based on field observations

Technical report

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iea wind

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Prepared for the

International Energy Agency Wind Implementing Agreement

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Purpose

Leading edge erosion (LEE) of wind turbine blades has been identified as a major factor in decreased wind turbine blade lifetimes and energy output over time. Accordingly, the International Energy Agency Wind Technology Collaboration Programme (IEA Wind TCP) has created the Task 46 to undertake cooperative research in the key topic of blade erosion. Participants in the task are given in Table 1.

The Task 46 under IEA Wind TCP is designed to improve understanding of the drivers of LEE, the geospatial and temporal variability in erosive events; the impact of LEE on the performance of wind plants and the cost/benefit of proposed mitigation strategies. Furthermore Task 46 seeks to increase the knowledge about erosion mechanics and the material properties at different scales, which drive the observable erosion resistance. Finally, the Task aims to identify the laboratory test setups which reproduce faithfully the failure modes observed in the field in the different protective solutions.

This report is a product of Work Package 3: Wind Turbine Operation with Erosion**.**

The objectives of the work summarized in this report are to:

- Assess the accuracy of LEE performance loss model based on field observations.

Table 1 IEA Wind Task 46 Participants.

Country	Contracting Party	Active Organizations
Belgium	The Federal Public Service of Economy, SMEs, Self-Employed and Energy	Engie
Canada	Natural Resources Canada	WEICan
Denmark	Danish Energy Agency	DTU (OA), Hempel, Ørsted A/S, PowerCurve, Siemens Gamesa Renewable Energy
Finland	Business Finland	VTT
Germany	Federal Ministry for Economic Affairs and Energy	Fraunhofer IWES, Covestro, Emil Frei (Freilacke), Nordex Energy SE, RWE, DNV, Mankiewicz, Henkel
Ireland	Sustainable Energy Authority of Ireland	South East Technology University, University of Galway, University of Limerick
Japan	New Energy and Industrial Technology Development Organization	AIST, Asahi Rubber Inc., Osaka University, Tokyo Gas Co.
Netherlands	Netherlands Enterprise Agency	TU Delft, TNO
Norway	Norwegian Water Resources and Energy Directorate	Equinor, University of Bergen, Statkraft
Spain	CIEMAT	CENER, Aerox, CEU Cardenal Herrera University, Nordex Energy Spain
United Kingdom	Offshore Renewable Energy Catapult	ORE Catapult, University of Bristol, Lancaster University, Imperial College London, Ilosta, Vestas
United States	U. S. Department of Energy	Cornell University, Sandia National Laboratories, 3M

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Executive Summary

The primary objective of validating leading edge erosion performance loss is to obtain reliable data on power loss and annual energy production loss over time. Achieving this goal necessitates comprehensive turbine data, accurate observation data, and reliable models for comparison, which are often limited in open research.

Two field observation studies aimed to validate power loss models due to erosion but did not provide sufficient data for conclusive model validation. The Sandia Field Experiment Erosion Study analyzed data from two turbine pairs with Class 2-4 erosion with baseline data over several years. The study fitted power curves using average wind speed bins and regression models, revealing slight differences in power performance between repaired and unrepaired turbines. The resulting relative power difference was not statistically significant, but the results were used to estimate the required number of turbine pair samples to reach a desired probability of detecting the power change from erosion damage.

The DTU Study, conducted by Malik and Bak, examined the degradation of full-scale wind turbine performance due to LEE, turbulence, and other factors through three separate studies. These studies demonstrated the complexity of analyzing measurement data from full-scale turbines, the unexpected performance increases due to maintenance activities, and the potential of the Blade Tip Torsion sensor for detecting power losses. These findings underscore the challenges in accurately measuring and validating power loss due to LEE, emphasizing the need for comprehensive analysis and validation in real-world conditions.

Current methods for validating power loss and AEP loss due to LEE involve using calibrated computational models or high-quality wind tunnel measurements to predict the effects of erosion on airfoil performance. These predictions are then applied in rotor simulations to estimate power loss, considering the interaction of the turbine controller with turbulent winds and the impact of erosion on lift and drag. The Phase 1 Aerodynamic Benchmark highlights the use of computational aerodynamics codes to assess the impairment of wind turbine blades caused by erosion, with high-fidelity models like Navier-Stokes CFD codes and lower-fidelity potential flow models.

The LERCat project aims to expand testing and simulations on real LER topologies, developing a workflow to extract and analyze these topologies from full-scale turbine blades. The project also includes wind tunnel measurements on various LER configurations to create a categorization scheme linking LER to aerodynamic loss, which will aid in AEP loss calculations.

Future work involves further aerodynamic benchmarking, relating erosion categories to roughness parameterization, and designing experiments to validate LEE performance loss models based on field observations. This will address data gaps and measurement uncertainties, ultimately leading to more accurate predictions and improved validation of power and AEP loss due to LEE.

1. Introduction

The ultimate goal to validate leading edge erosion (LEE) performance loss is to have power loss and annual energy production (AEP) loss data over time. Estimating such loss also requires a turbine with sufficient data on the turbine, wind, and blade condition to input to a model along with accurate observation data sufficient to compare to the model results for validation. Unfortunately, turbine information is often too limited to accurately model production turbines for open research purposes and field measurements have uncertainty too high to measure power and AEP loss due to erosion for the high mark of model validation. This does not mean that the power and AEP loss are not present, just that it falls within the common 5% uncertainty on measurements of these values. However, 5% AEP loss is very significant, even <1% is of noticeable concern for a wind plant owner.

2. Progress of Field Observation Studies

Two studies have sought to attempt to validate models of power loss due to erosion based on field observations. Both studies have provided great insight into the drivers of erosion performance loss, but neither has successfully provided data sufficient for model validation.

2.1. Sandia Field Experiment Erosion Study

This work describes the analysis of field data to determine the impact of erosion on wind turbines in the field over time. Seven turbine pairs that have developed Class 2 to Class 4 erosion over a 10-year operational life are analyzed. SCADA data from the turbines and nearby meteorological towers are used in conjunction to reduce measurement uncertainty.

Previous studies have investigated the impact of erosion on blade aerodynamics by placing models of eroded airfoils in wind tunnels and measuring the lift and drag as compared to clean models (Sareen, Sapre, & Selig, 2014) (Ehrmann R. S., et al., 2013) (Ehrmann & White, 2014) (Ehrmann & White, Effect of Blade Roughness on Transition and Wind Turbine Performance., 2015). The results are then used in overall rotor performance models and combined with operational profiles to predict AEP. The findings indicate up to 5% decreases in AEP are possible. Recent work has also examined uncertainty in these predictions due to erosion rate, extent, and category (Maniaci, Westergaard, Hsieh, & Paquette, 2020). In the present work, SCADA data was analyzed to determine the decrease in performance over time for a subset of seven turbine pairs of turbines that have been in operation for approximately 10 years. The turbine pairs were selected to have Class 2-4 levels of erosion. The results are then used along with expected mean power loss from modeling to determine the statistical significance of the data and to estimate the required number of samples needed to reach a given level of uncertainty.

2.1.1. Field Data Analysis Introduction

An analysis was performed on archival SCADA data collected from wind turbines and nearby meteorological towers at an operating wind farm (Maniaci, Dowden, Paquette, & Hsieh, 2021) (Maniaci, Reyna, Davies, & Paquette, 2023). The turbines were identified by the owner as having leading edge erosion (LEE) ranging from category 2 to 4. The objective of this analysis was to evaluate the relative performance of pairs of turbines with leading edge erosion to identify the impact of repair (versus no repair) on power production.

2.1.2. Data Input and Filter Method

Local meteorological tower data and archival wind plant SCADA data were utilized from turbines classified as having undergone Category 4 erosion. Measurements, recorded in 10-minute intervals, included wind speed, wind direction, temperature, atmospheric pressure, power production, nacelle direction, and other channels observed from January 2016 to June 2020. Field observations for power production were compared to expected values derived from the rated power curve for the associated turbine model. The analysis involved linearly approximating field values to the rated curve and calculating the difference between observed power and expected power values, filtering out records with higher discrepancies. Differences between wind speeds recorded at turbine hub height and those from the nearby meteorological tower were also considered. Records with turbine wind speeds exhibiting absolute differences greater than 1.5 m/s from meteorological tower wind speeds were filtered out. After examining the distribution of power differences, observations with high discrepancies were collected and averaged in 10-minute records. The analysis targeted six turbines at the partner wind plant classified as having Category 4 level erosion.

2.1.3. Fitting Power Curves Using Average Wind Speed Bins

For each turbine, all power observations were averaged across 1% wind speed bins to produce binned average wind speed power curves. These curves were compared with a reference power curve, which recorded expected power values for 0.5 m/s divisions ranging from 3 to 15 m/s. Binned power curves were generated for observations before and after each turbine repair date. Data was obtained from the NOAA local climatological data station near the wind plant to estimate quantities not measured by the local wind plant meteorological tower.

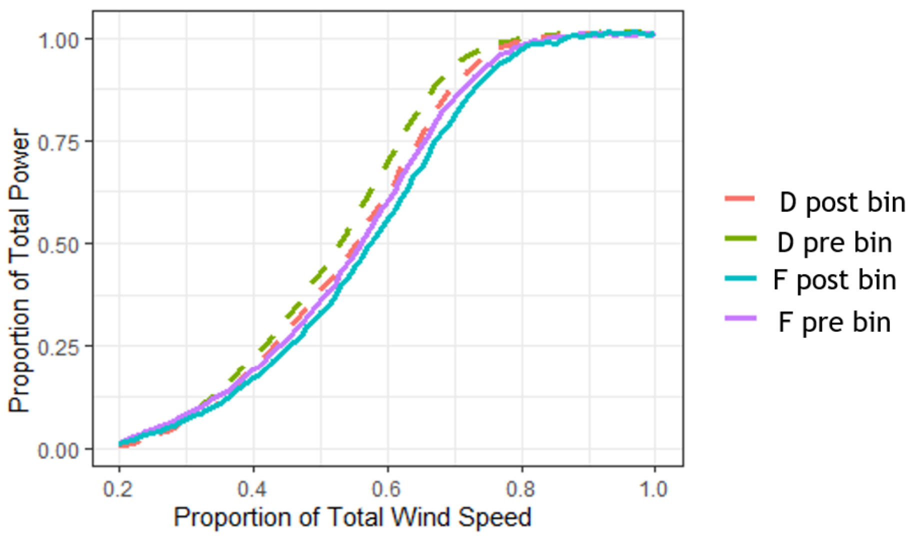


Figure 1. Average wind speed binned power curves for turbines D and F.

2.1.4. Fitting Power Curves Using Regression Models

Additionally, for each month, power curves were graphed for each turbine and fitted using a three-parameter logistic function shown in Equation 1. Logistic regression curves were produced for observations before and after each turbine repair date, resulting in the curves shown in Figure 2. This method was employed to capture the slope and boundary conditions of the wind power curve, where the slope is zero up to the cut-in wind speed and at rated wind speed. Values were filtered starting at a cut-in wind speed of 3 m/s, corresponding to a normalized value of 20% of the rated wind speed of 15 m/s.

Equation 1

$$P = \frac{\phi_1}{1 + \exp\left(\frac{\phi_2 - S}{\phi_3}\right)}$$

P = power
S = speed
Φ_i = smoothing parameter

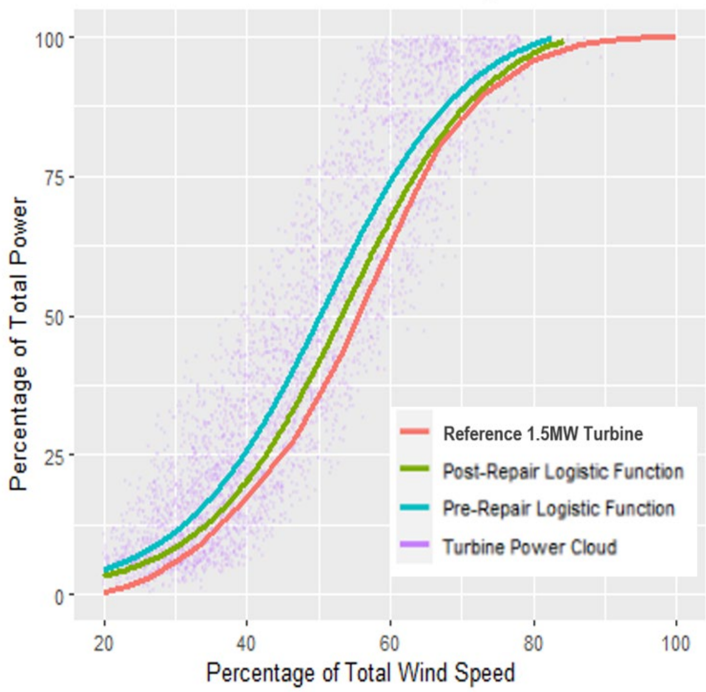


Figure 2. Regression power curves produced for observations before and after each turbine repair date.

2.1.5. Comparing Turbine Pairs – Overall Power Curves

While the power curves for the turbines appeared similar, slight differences in the overall area toward Region III contributed to greater differences in power performance. Overall, the unrepaired control turbines (B and D) generated less power after the repairs relative to turbines C and F. To assess the effectiveness of the repairs, the relative power loss for both turbines was compared. If turbines C and F exhibited better relative performance, it could be concluded that the repairs were effective. Monthly power curves were graphed for each turbine and fitted using the three-parameter logistic function, revealing a greater area of the post-repair binned power curve depending on the effect of the repair.

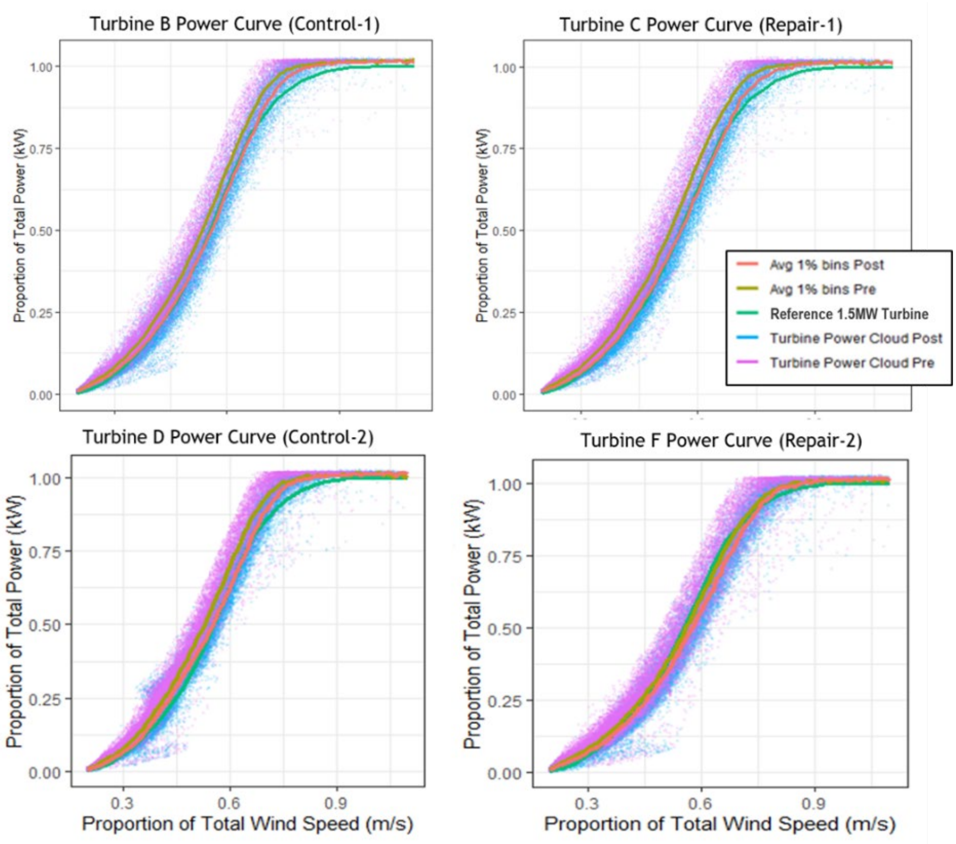


Figure 3. Comparison of power from turbine pairs. Power normalized by rated power and wind speed normalized by the rated wind speed.

2.1.6. Comparing Turbine Pairs – Relative Power Differences

The relative power difference between each turbine pair before and after the repair events is shown in Figure 4. Turbine C was generating 1-2% more power for the same wind speed in middling wind speeds, with approximately equal production at the extremes. After repairs, this advantage largely disappeared, resulting in a net loss of relative power gain. Turbine F was generating 5-8% less power for the same wind speed in middling wind speeds, with approximately equal production at the extremes. After repairs, this disadvantage was slightly mitigated, resulting in a net gain in relative power of 1-2% across middling wind speeds. Power was normalized by the reference power curve.

The comparative turbine analysis of the field data demonstrated a strong dependence on correcting for turbine-to-turbine power production variability, with one turbine pair showing a relative improvement after the repair and another showing a relative loss. A longer period of post-repair data may help to test corrections for the effects of seasonal variability, although other changes to the turbine over time may mitigate the value of a longer sampling period. The impact of the LEE repair appears most noticeable in middle wind speeds, primarily in upper Region II operation. The field data analysis indicated a peak power loss lower than model predictions in repaired versus unrepaired power at all wind speeds, with higher discrepancies near cut-in and rated wind speeds.

Recommendations for future work will include analysis over a longer time period and using more turbines, as well as developing a probabilistic simulation of site conditions and an uncertainty analysis of the field data for a more direct comparative analysis.

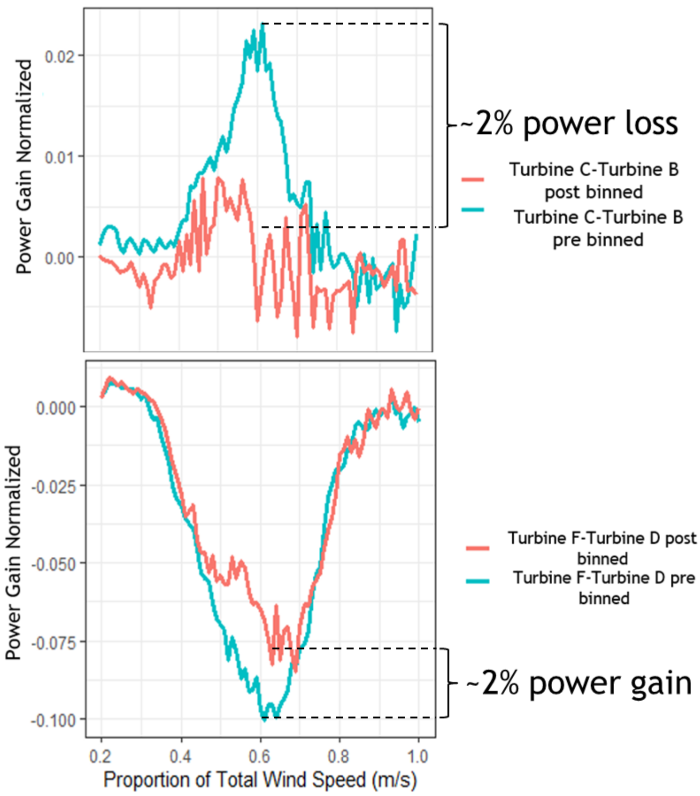


Figure 4. Relative power difference between turbine pairs C and B (top) and D and F (bottom).

2.1.7. Estimation of Required Turbine Pair Sample Size

Although the relative power difference between the two turbine pairs was not in agreement, the results can be used along with an estimate of the expected mean power difference to predict the number of turbine pair samples needed to reach a statistically meaningful result. The likelihood of detecting an increase in the relative power output of a set of turbine pair samples with a given sample size was modeled using a one-sample t-test of differences, as shown in Figure 5. The mean difference was assumed to be 3% based on modeling results (Maniaci, Westergaard, Hsieh, & Paquette, 2020). The corrected standard deviation was estimated to be 2.8%. Based on two turbine pair samples with +2% and -2% change in power, the effect size was calculated to be 1.06 using Equation 2. The results shown in Figure 5 indicate that ten turbine pair samples would be needed to achieve a greater than 90% probability of detecting a 3% change in power due to erosion repairs, given a 2.8% power difference standard deviation.

Equation 2

$$Effect\ size = \frac{Expected\ power\ difference}{Standard\ deviation\ in\ power\ difference} = \frac{3\%}{2.83\%} = 1.06$$

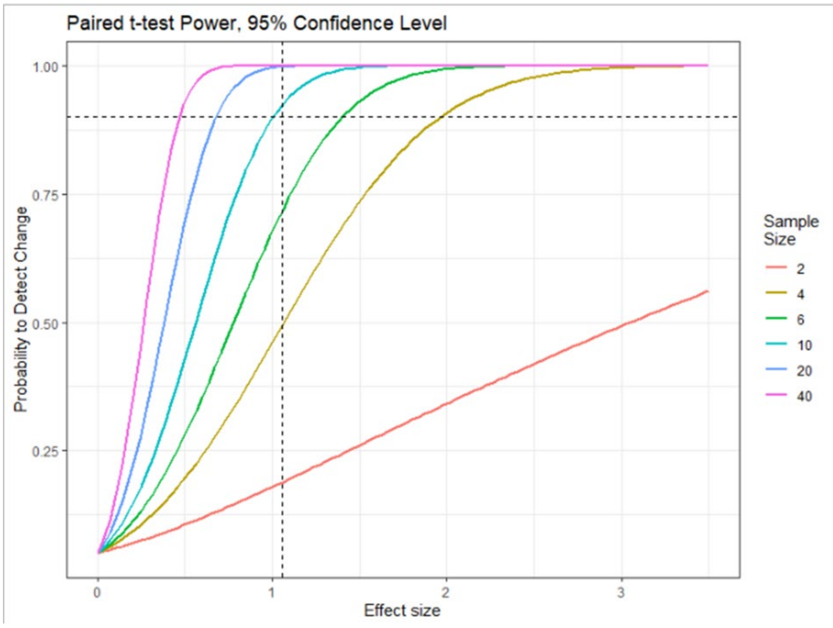


Figure 5. Required turbine pair sample size as a function of the probability to detect an increase in the relative power output of a set of turbine pair samples, modeled using a one-sample t-test of differences.

2.1.8. Conclusion and Future Work

The comparative analysis of the field data revealed a strong dependence on correcting for (or controlling) turbine-to-turbine power production variability, with one turbine pair showing a relative improvement after the repair and another showing a relative loss. A longer period of post-repair data is necessary to test corrections for the effects of seasonal variability. The impact of the LEE repair appears most noticeable in middle wind speeds, primarily in upper Region II operation. The field data analysis indicated a peak power loss lower than model predictions in repaired versus unrepaired power at all wind speeds, with higher discrepancies near cut-in and rated wind speeds.

Continued analysis over a longer time period and using more turbine pairs is necessary. Developing a probabilistic simulation of site conditions and an uncertainty analysis of the field data for a more direct comparative analysis, including uncertainty in the repaired condition, will be important. Additionally, releasing field data power performance analysis software openly and supporting its use by external partners will be beneficial.

This report summarizes the findings from the analysis of turbine performance data and highlights the need for further investigation to validate the results and understand the long-term effects of repairs on turbine efficiency.

2.2. Vattenfall/DTU Study

Investigations of degradation of the performance of full scale wind turbines have been carried out in studies by Malik and Bak (Malik & Bak, 2025A) (Malik & Bak, 2024) (Malik & Bak, 2025B). Three studies have been carried out: 1) A study on the challenges in detecting energy losses where the effect of erosion, turbulence and time averaging are investigated (Malik & Bak, 2025A), 2) A study where energy losses are detected with a method where the fluctuating wind speed is omitted (Malik & Bak, 2024) and 3) A study where it is investigated if other sensors than the power can be used to detect performance losses (Malik & Bak, 2025B).

The first study is based on aeroelastic computations of a real wind turbine with all its control included. This is to be able to highlight the challenges when measurement data from full scale wind turbines should be analyzed. An example of many from this study is shown in Figure 6. Here, it is shown how the power is predicted using the aeroelastic tool HAWC2 when three different turbulence intensities are assumed: 0%, 6% and 20%. The low turbulence intensity, Ti=0%, is often what will be the result when analyzing pure aerodynamic performance using Blade Element Momentum (BEM) methods and Computational Fluid Dynamics (CFD) in steady state. However, in real life the turbulence levels are e.g. 6% that is fairly low but also 20% that is rather high. When comparing the differences in power due to turbulence with the differences due to different roughness levels it is clear that turbulence is a very important factor. Thus, in the study three different levels of erosion are shown: 1) No erosion (Clean), light erosion (corresponding to a sand paper roughness of P400) and heavy erosion (corresponding to a sand paper roughness of P40).

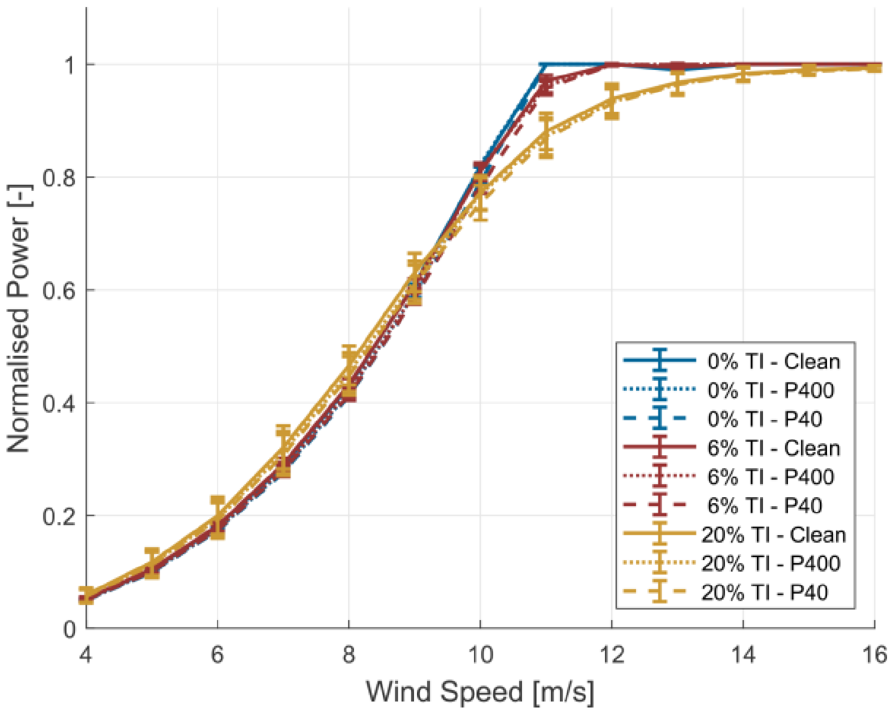


Figure 6. Normalized power for a MW wind turbine as a function of wind speed. The performance for 0%, 6% and 20% turbulence intensity is shown, where also three different levels of aerodynamic performance are shown: A clean blade, a blade with a lightly eroded leading edge corresponding to a sand roughness of P400 and a blade with a heavily eroded leading edge corresponding to a sand roughness of P40. Illustration from (Malik & Bak, 2025A).

In Figure 6 it can be seen that the performance at low wind speeds at e.g. 7m/s shows higher power at higher turbulence levels than at lower turbulence levels despite the fact that the blade is heavily eroded. This illustrates the challenge to measure the power loss from full scale wind turbines because the turbulence intensity is not constant but varying from day to day, hour to hour and minute to minute.

The second study is based on an analysis of measurements from an offshore wind farm. Since power as a function is uncertain as shown in the first part explained above, another way of investigating this was explored. An example is shown in Figure 7 where the normalized generator speed is shown as a function of the normalized power where each curve is an average for each year from initiation of the wind farm. To understand this plot it is important to be aware that the faster a rotor is rotating at the same power the less efficient it is because power is a product of torque and rotational speed. Therefore, the faster it rotates the lower the torque is. The curves in the lower end of the band represent the most efficient performance. It was unexpected that the efficiency was increasing over time from year 1 to year 7 as it is seen in the figure.

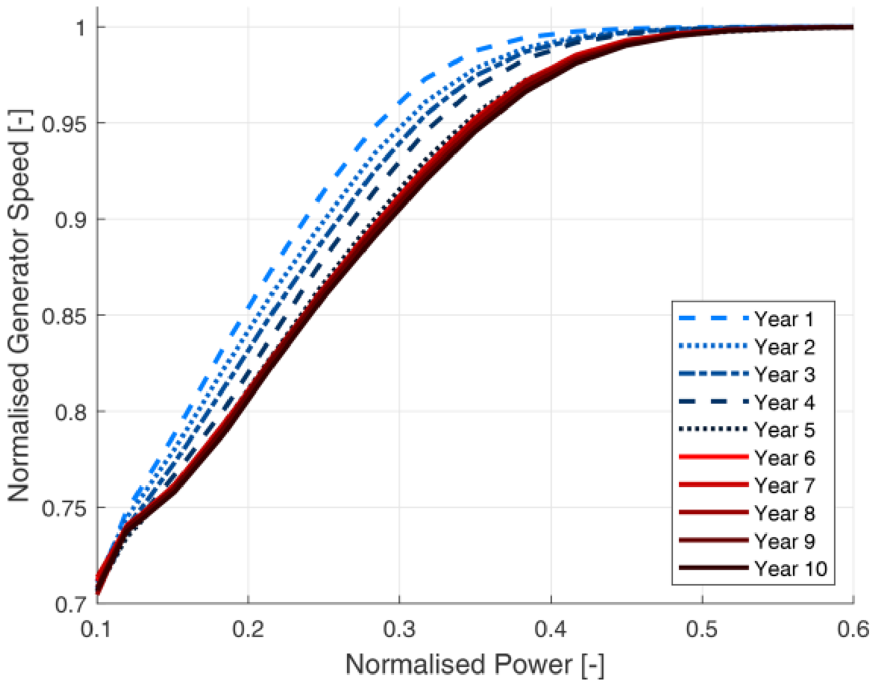


Figure 7 Normalized generator speed as a function of normalized power for each year for a wind turbine. Illustration from (Malik & Bak, 2024).

The reason for the unexpected increase in performance was investigated where it was found that many different maintenance activities had been carried out. Figure 8 shows how different activities have affected the performance. The values along the y-axis are the area below the curve shown in Figure 7. Values less than 0 (zero) show improved performance and greater than 0 (zero) show decreased performance. From the different examples in Figure 8 one of those is “Software update” that shows an increase in performance, which explains the increase in performance the first years of operation.

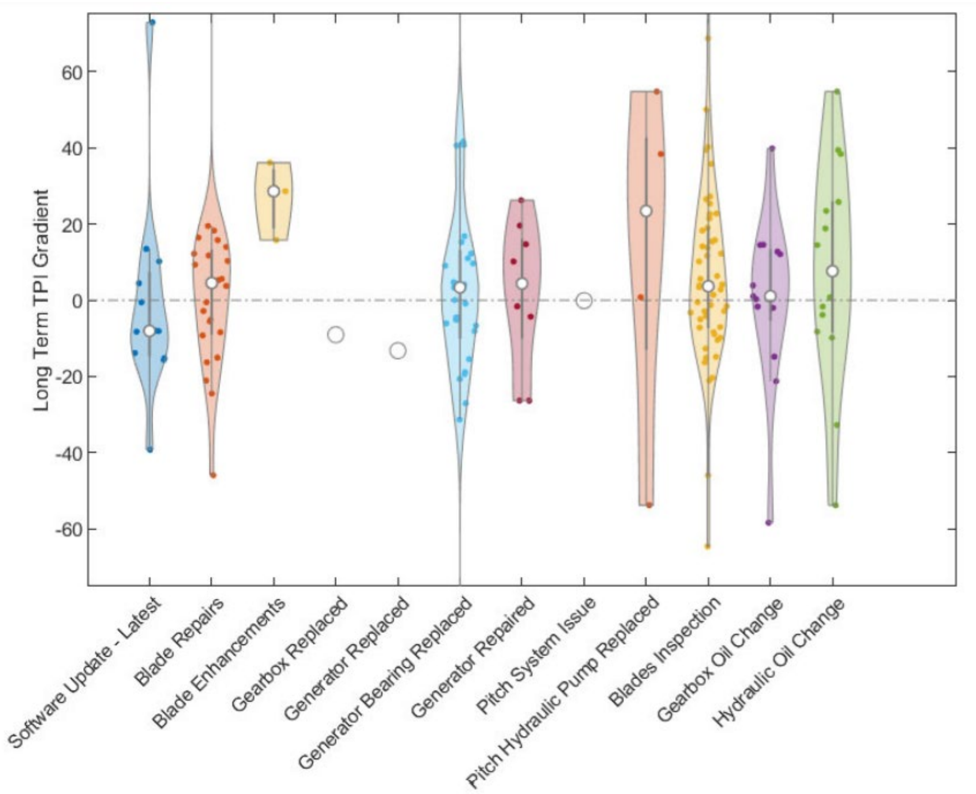


Figure 8 Violin plots of TPI (Turbine Performance Integral) plotted in connection to each maintenance activity. Illustration from (Malik & Bak, 2024).

This study showed the complexity in detecting energy losses because there can be many reasons for the energy loss to appear.

The third study was based on a study on how different sensors can be used to detect degradation of the performance. An example from this study is a comparison of the difference in the signals from sensors from an aeroelastic computation with and without erosion at the leading edge, see Figure 9. In the figure there is much information where each sensor is shown along the y-axis and the wind speed is shown along the x-axis. Most important from the plot is that e.g. the Blade Tip Torsion sensor shows the most significant difference and therefore could be a candidate for a sensor to use to detect power losses. This should however be validated in full scale because this study is based on aeroelastic computations.

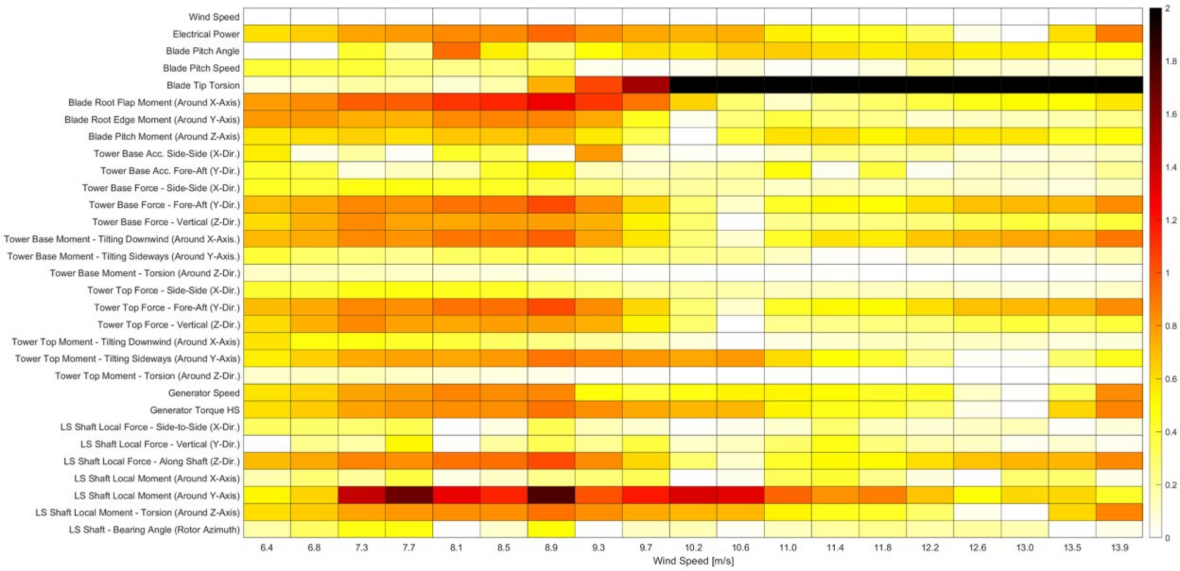


Figure 9 Heat map of the difference in performance for rough (P40) versus clean conditions as a function of wind speed for multiple sensors at a turbulence intensity of 12 %. Illustration from (Malik & Bak, 2025B).

The above descriptions of the three studies are examples out of all the work that was carried out. Therefore, for a complete overview of the work there are references to (Malik & Bak, 2025A) (Malik & Bak, 2024) and (Malik & Bak, 2025B).

3. Current Methods for Erosion Power and AEP Loss Validation

Power loss and AEP loss are very important to predict despite the lack of direct validation data. The current state of the art in predicting these values is to use either calibrated computational models of the effect of erosion on airfoil force data or to use high quality wind tunnel measurements of such effects (Maniaci, Forsting, Barlas, Bak, & Olsen, 2025).

A spanwise damage model is then used to distribute the airfoil polar data along the blade span. The spanwise eroded airfoil data is then used in aeroelastic simulations of the rotor to predict the power loss with erosion. Such predictions can include the interaction of the controller with simulated turbulent winds and the change of the controller response for pitch and speed regulation of the turbine with the effect of erosion on the airfoil lift and drag.

3.1. Aerodynamic Benchmark Summary

In order to validate the performance or current state of the art models of the effect of erosion and roughness on airfoil lift and drag, a benchmark has been undertaken as part of the work package 3 activities, which is summarized in a separate report (Campobasso, Castorrini, Bretos, Mendez, & Maniaci, 2025). The report presents an initial assessment of the predictive capabilities of computational aerodynamics codes used in industry and academia for predicting the aerodynamic performance impairment of wind turbine blades caused by erosion. A range of model fidelity is considered in the exercise, with the high-fidelity being Navier-Stokes computational fluid dynamics codes. The lower-fidelity methods are potential flow models coupled to integral boundary layer equations and a transition model, augmented with empirical correlations. The test cases used for the study consist of wind tunnel aerodynamic experiments carried out in state-of-the-art European and American wind tunnels. The results of this investigation are relevant to predicting the turbine power and energy yield loss caused by erosion.

3.2. LERCat Aerodynamic Benchmark Summary

As mentioned, simulations and wind tunnel tests on high quality LER topologies are needed in order to get good estimations of the AEP loss on turbines. There is much past work on wind tunnel testing of erosion, e.g. (Ehrmann R. S., et al., 2013), (Gaudern, 2014), (Gutiérrez, Llórente, Echeverría, & Ragni, 2020), (Kruse, Bak, & Olsen, 2021), (Maniaci, et al., 2016), (Sareen, Sapre, & Selig, 2014), (Veraart, 2017) and (White, et al., 2011). However, there is still a need for more data on this, as the previous studies are to some degree made with idealized LER topologies inspired by LER on turbine blades or a limited number (1-2) of real LER topologies.

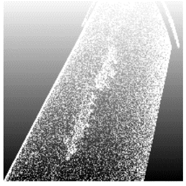
In the LERCat project (Leading Edge Roughness Categorization, (LERCat, 2023)) one of the objectives is to expand the number of tests and simulations on real LER topologies.

In order to extract real LER topologies from full scale wind turbine blades a workflow was developed within the project. The workflow is outlined in Figure 10 and more details are found in (Meyer Forsting, et al., 2024). The starting point is to identify LER on wind turbine blades, then a silicone imprint and a plaster casting is made from the damage. The casting is scanned with a high resolution hand scanner (ZEISS T-SCAN hawk 2). The point cloud from the scan is analyzed in order to get the LER topology defined as the difference between the manufactured (un-damaged) shape and the scan. This is not a trivial task as the reference airfoil is often not known. Even if it is, there is most likely differences between the nominal shape and the manufactured shape due to the accuracy of the blade mould or postprocessing of the blade, e.g. grinding of the LE joint. Hence, the reference shape needs to be estimated, which can be done in different ways. A promising method is to fit a convex hull on LE part of the scan, which has been used to extract the LER patch in Figure 10.

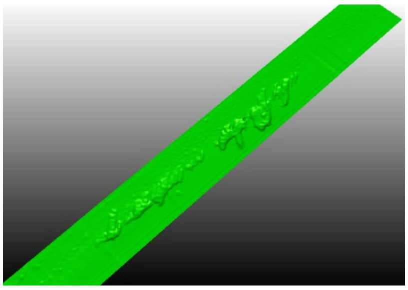
1: Wind turbine blade with LER

2: Mould for silicone imprint on the blade

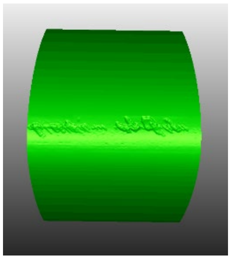
3: Plaster casting of the LER



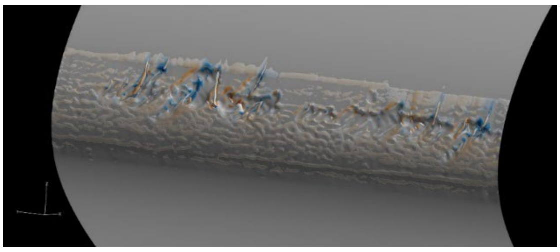
4: Point cloud form the scanning of the casting



5: Unfolded LER patch



6: LER patch wrapped around the FFA-W3-211 airfoil.



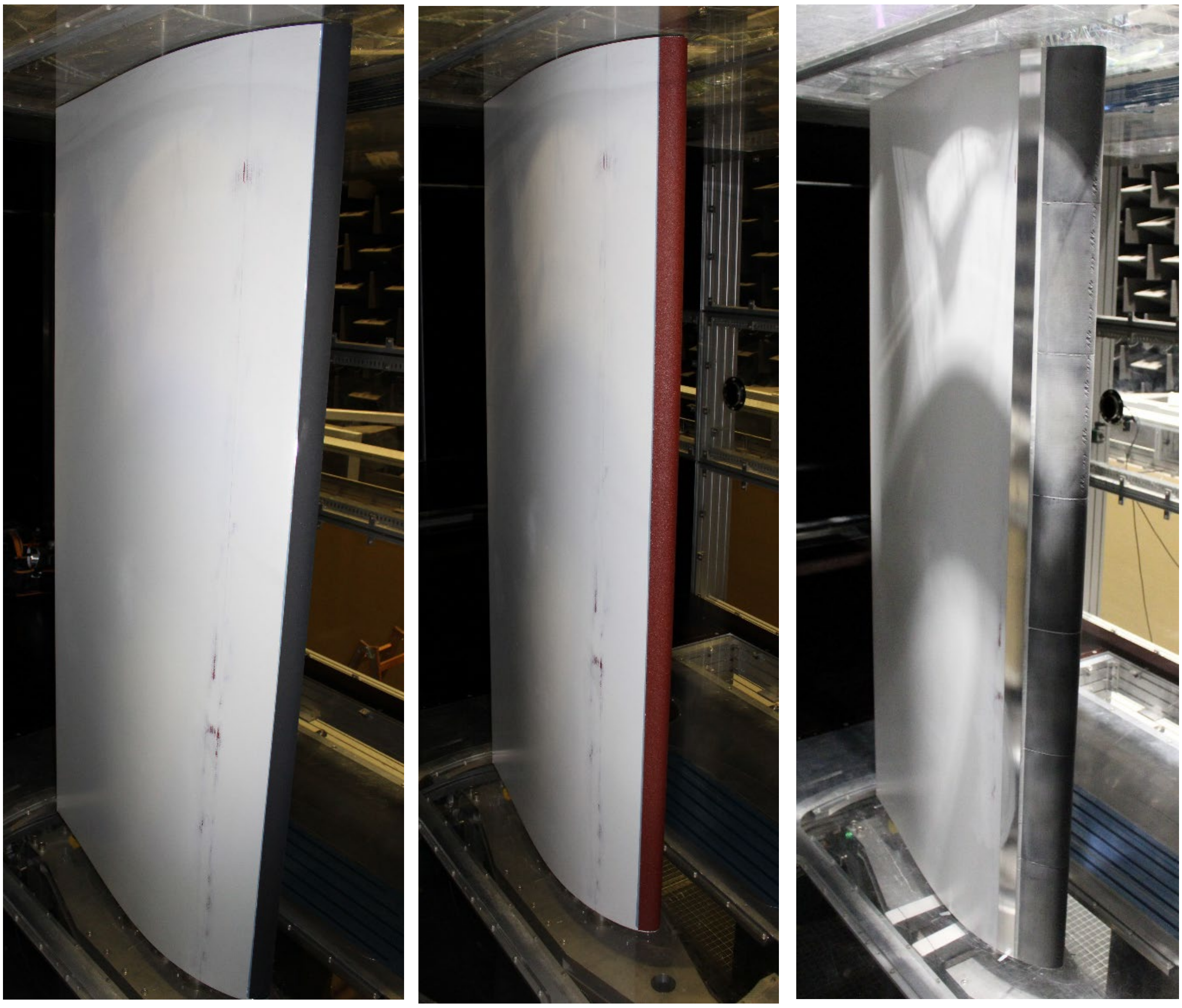
7a: CFD simulations

7b: Wind tunnel testing

Figure 10: Workflow for extracting the LER patches from a wind turbine blade.

For the IEA Task 46 Phase 2 CFD benchmark a number of the wind tunnel measurements on the FFA-W3-211 airfoil from the LERCat project is used. In addition to the clean and fully turbulent (i.e. zig-zag-tape in the wind tunnel tests) configurations, three LER configurations are used, i.e. wrap around sandpaper P400 and P40 and a realistic LER topology called LER-1. The tests are made at three Reynolds numbers; 3E6, 4.5E6 and 6E6. Figure 11 and Figure 12 show the model with the five configurations in the Poul la Cour wind Tunnel (PLCT).

Figure 11: FFA-W3-211 in the PLCT clean (left) and zigzag-tape (right).



Sandpaper P400 **Sandpaper P40** **LER-1**

Figure 12: FFA-W3-211 in the PLCT with different LEE applied

Based on the performed simulations and wind tunnel tests on real LER a categorization scheme that links LER to a sectional aerodynamic loss is developed in the LERCat project. A draft of the scheme is seen in Figure 13. The final outline of the categorization scheme is still work in progress, as the project is running through June 2025. The categorization scheme makes it possible to estimate the sectional aerodynamic performance of a blade section from pictures obtained during blade inspections. Combining these sectional losses gives the total loss of the turbine. Hence, the developed scheme links directly into the AEP loss calculations for the IEA Task 46 Phase 2.

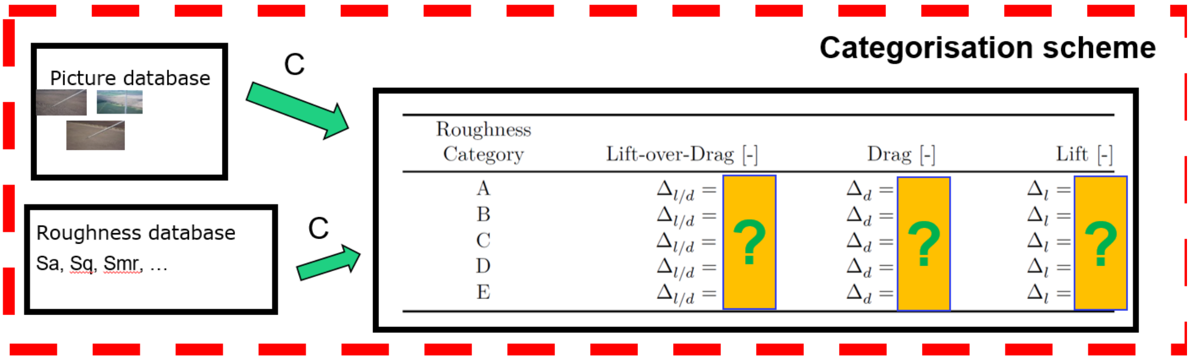


Figure 13: Draft of the LERCat categorization scheme that links blade inspections with a sectional aerodynamic loss.

4. Future Work

Although much has been learned from the past field studies of the performance impact of leading edge erosion, the community still lacks a dataset relating erosion levels of a rotor to the loss in power or AEP sufficient for the high statistical standards required for model validation. Two activities are planned in Phase 2 of IEA Wind Task 46 to continue the benchmarking work and to continue to grow toward AEP loss field validation:

1. Aerodynamic benchmarking and simulations, and reference models:
    - Aerodynamic benchmark on LERCat data;
    - Relate erosion categories to sandgrain roughness or other roughness parameterization. Application to canonical erosion progression (Springer model) along with actual observations of erosion;
    - Predict how higher Reynolds numbers (2-3 times wind tunnel tests) will impact aerodynamics of roughness and erosion, design experiment to address data gaps; and
    - Modelling and benchmark on aerodynamic effects and loss due to several representative LEP solutions.

2. Design of an experiment to assess the accuracy of LEE performance loss models based on field observations:
    - Model uncertainty of field measurements and in comparison, to model predictions; and
    - Publication on what is needed to measure AEP loss (2%) in uncertainty (3%)

5. Conclusions

Two field observation studies aimed to validate power loss models due to erosion but did not provide sufficient data for conclusive model validation. The Sandia Field Experiment Erosion Study analyzed SCADA data from two turbine pairs with Class 2-4 erosion with baseline data over several years. The resulting relative power difference was not statistically significant, but the results were used to estimate the required number of turbine pair samples to reach a desired probability of detecting the power change from erosion damage.

The DTU Study, conducted by Malik and Bak, examined the degradation of full-scale wind turbine performance due to LEE, turbulence, and other factors through three separate studies. These studies demonstrated the complexity of analyzing measurement data from full-scale turbines, the unexpected performance increases due to maintenance activities, and the potential of the Blade Tip Torsion sensor for detecting power losses. These findings underscore the challenges in accurately measuring and validating power loss due to LEE, emphasizing the need for comprehensive analysis and validation in real-world conditions.

The LERCat project aims to expand testing and simulations on real LER topologies, developing a workflow to extract and analyze these topologies from full-scale turbine blades. The project also includes wind tunnel measurements on various LER configurations to create a categorization scheme linking LER to aerodynamic loss, which will aid in AEP loss calculations.

Future work involves further aerodynamic benchmarking, relating erosion categories to roughness parameterization, and designing experiments to validate LEE performance loss models based on field observations. This will address data gaps and measurement uncertainties, ultimately leading to more accurate predictions and validations of power and AEP loss due to LEE. Enough has been learned from past work and what has been presented in this report to be able to converge on the requirements of a validation quality experiment for leading edge erosion power loss. The close alliance between industry and the researcher community enabled by IEA task collaboration will be required for such an experiment to be successful.

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