Modelling and Monitoring Erosion of the Leading Edge of Wind Turbine Blades

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Abstract: Leading edge surface erosion is an emerging issue in wind turbine blade reliability, causing reduction in power performance, aerodynamic loads imbalance, increased noise emission and ultimately additional maintenance costs, and if left untreated, leads to the compromise of the functionality of the blade. In this work, we first propose an empirical spatio-temporal stochastic model for simulating leading edge erosion, to be used in conjunction with aeroelastic simulations, and subsequently propose a deep learning model trained on simulated data, which aims to monitor leading edge erosion by detecting and classifying the degradation severity. The main ingredients of the model include a damage process that progresses at random times, across multiple discrete states characterized by a non-homogeneous compound Poisson process, which is used to describe the random and time-dependent degradation of the blade surface, thus implicitly affecting its aerodynamic properties. The model allows for one, or more, zones along the span of the blades to be independently affected by erosion. The proposed model accounts for uncertainties in the local airfoil aerodynamics via parameterization of the lift and drag coefficients curves. The proposed model is used to generate a stochastic ensemble of degrading airfoil aerodynamic polars, for use in forward aero-servo-elastic simulations, where we compute the effect of leading edge erosion degradation on the dynamic response of a wind turbine under varying turbulent input inflow conditions. The dynamic response is chosen a defining output as this relates to the output variable that is most commonly monitored under a Structural Health Monitoring (SHM) regime. In this context, we further propose an approach for spatio-temporal dependent diagnostics of leading erosion, namely, a deep learning attention-based Transformer, which we modify for classification tasks on slow degradation processes with long sequence multivariate time-series as inputs. We perform multiple sets of numerical experiments, aiming to evaluate the Transformer for diagnostics and assess its limitations. The results reveal Transformers as a potent method for diagnosis of such degradation processes. The attention-based mechanism allows the network to focus on different features at different time intervals for better prediction accuracy, especially for long time-series sequences representing a slow degradation process.

Keywords: Wind turbine; Structural Monitoring; Leading edge erosion; Poisson process; aeroelastic simulations; Lift and drag; Deep learning; Transformer; Diagnostics

29 **Nomenclature**

30	α	Wind shear exponent
31	$\mathbb{E}$	Expected value of a random variable
32	$\mathbb{V}$	Variance of a random variable
33	σ	Turbulence
34	C_D	Aerodynamic drag coefficient
35	C_L	Aerodynamic lift coefficient
36	C_m	Aerodynamic moment coefficient
37	C_p	Aerodynamic pressure coefficient
38	<i>CNN</i>	Convolutional Neural Network
39	<i>EZ</i>	Eroding Zone
40	<i>LE</i>	Leading Edge
41	<i>LEE</i>	Leading Edge Erosion
42	<i>MLP</i>	Multilayer Perceptron
43	<i>MTS</i>	Multivariate time-series
44	<i>NHCPP</i>	Non-Homogeneous Compound Poisson Process
45	<i>O&M</i>	Operation and Maintenance
46	R	Blade radius
47	<i>RNN</i>	Recurrent Neural Network
48	<i>RV</i>	Random Variable
49	<i>SHM</i>	Structural Health Monitoring
50	T_i	Turbulence intensity
51	U	Mean wind speed
52	<i>WT</i>	Wind Turbine

53 **1 Introduction**

54 This work is motivated by current efforts on development of a novel micro-electro-
 55 mechanical monitoring system based on aerodynamic surface pressure and aero-acoustic
 56 measurements for Structural Health Monitoring of wind turbine blades, as part of
 57 the Aerosense project¹. Sensing nodes are distributed along the span of the blade
 58 delivering measurements of local sectional aerodynamic pressure distributions, aero-
 59 acoustic and acceleration signals (see illustration in Figure 1). Assuming availability of
 60 such a monitoring system, we here propose an approach to the modelling and diagnostics
 61 of erosion of the leading edge for wind turbine blades.

¹ <https://www.aerosense.ai/>

Figure 1. Illustration of Aerosense, a novel MEMS-based aerodynamic surface pressure and aero-acoustic measurement system for wind turbines blades.

Bogdanoff and Kozin (1985) [1] define cumulative damage as the “irreversible accumulation of damage throughout life that ultimately leads to failure”. Leading edge erosion of a wind turbine blade represents such a process, albeit at slow degradation rates, with effects slow to manifest and even harder to detect early on. Most diagnostic techniques today rely on direct visual inspection[2], image processing [3], and statistical analysis, e.g. regression or clustering of SCADA output, such as blade pitch, rotor speed or electrical power [4,5]. Visual inspection and image acquisition imply stopping the turbines, resulting in loss of power production. More importantly, they give a local (both spatial and temporal) snapshot of the erosion condition without a direct link to the historical progression of the degradation and how it relates to environmental and operational conditions. Even though it is better positioned to discriminate the environmental and operational conditions versus degradation process, long term SCADA based statistical analysis invariably do not possess the necessary resolution to determine accurately the severity and spatial extent of erosion on the blades. A gap therefore exists in the field of spatio-temporal modelling and diagnostics of leading edge erosion for wind turbines rotor blades. In this work, we are particularly interested in leveraging time series emanating from the novel Aerosense based aerodynamic surface pressure monitoring system for wind turbines blades. The aim is to (1) detect the occurrence of erosion and (2) classify the severity (intensity) of erosion. This could be regarded as either the inverse problem of reconstruction for the lift and drag coefficients, or a problem of finding the optimal discriminants for erosion versus other effects from time series response signals. This is a time dependent multi-class and multi-label problem. To tackle this problem and build meaningful diagnostics models, realistic time-series data is required for training. Our options are either collect multi-year field data, where the rotor blade are known to undergo leading edge erosion, or develop a numerical model of leading edge erosion coupled to an aeroelastic simulator. As data availability for such systems is often limited and restricted by data sharing protocols, we here opt for the route of simulation, with the additional benefit of delivering a model that can be used for simulating such slow leading edge erosion degradation processes.

Towards accomplishing the goal of diagnostics and inference of erosion of the leading edge of wind turbine blades, this work makes the following contributions:

- We develop a stochastic spatio-temporal erosion model of the leading edge of wind turbine blades, which is characterized by a non-homogeneous compound Poisson process across discrete states, embedded in a generator of stochastic ensemble of degrading airfoil aerodynamic polars for use in forward aero-servo-elastic simulations. The coupled model is able to compute the aeroelastic non-stationary response of a wind turbine, thus reflecting its behaviour under the effect of leading edge erosion

- 99 and varying turbulent input inflow conditions over long period of degradation
 100 time horizon.
- 101 • We adapt a deep learning multi-variate time-series based Transformer with atten-
 102 tion mechanism to detect and classify long-term and slow leading edge erosion
 103 processes assuming availability of on-blade sectional monitoring data, under short
 104 and long-term wind inflow uncertainties and inject direct aerodynamic uncertain-
 105 ties on the lift and drag coefficients of the airfoil sections along the span of the
 106 blade.

A graphical abstract of this research is presented in Figure 2.

Figure 2. A graphical abstract of modelling and diagnosing erosion of the leading edge of wind turbine blades.

107

108 The remainder of this article is organized as follows. In Section 2 we offer a review
 109 of the state of the art in modelling and diagnostics of leading edge erosion. In Section 3
 110 we present the details of the spatio-temporal stochastic model for leading edge erosion.
 111 In section 4 we present the uncertainty modelling and the aeroelastic simulations setup.
 112 In section 5 we elaborate the theory of the deep learning multi-variate time-series based
 113 Transformer for diagnostics and inference. In Section 6, we illustrate the novelty and
 114 principles of the proposed framework on a simulations-based application and further
 115 provide discussions and list the limitations in Section 7.

116 2 Review of Prior Art

117 We first review modelling approaches of leading edge erosion in conjunction with
 118 aeroelastic simulations and subsequently assess the state-of-the-art in diagnostics meth-
 119 ods.

120 2.1 Modelling leading edge erosion

121 Several studies have quantified the impact of leading edge erosion on aerodynamic
 122 and aeroelastic performance of wind turbines.

The general thread in the first set of studies amounts to describing the constitutive laws, physical processes and instigators at the micro scale resulting in surface erosion/degradation and the various stages and types of erosion severity e.g., [6–10]. Such models incorporate the effect of wind speed, air density, particle size, incubation time, and erosion intensity due to rainfall, snowfall, sea spray, and fog. It is unclear however how the micro-scale models couple to the macroscale aspects of leading edge erosion and consequently the effect on turbine performance.

The second set of studies quantifies the impact on wind turbine performance via computational approaches (aeroelastic or CFD simulations) or extensive experimental campaigns in wind tunnels, coupled to uncertainty propagation schemes e.g., [11–16]. The limitations in all these works is that they do not allow for multiple zones along the span of the blades to be independently affected by stochastic erosion processes.

Bortolotti *et al.* [17] proposes a simple stochastic model to describe the extent of blade span-wise degradation due to leading edge erosion via a single factor that is assumed to follow a truncated beta distribution. However, the long term temporal degradation process of blade leading edge is not accounted for. Dimitrov [18] describes a first attempt to introduce temporal progression to the damage growth for leading edge erosion due to rainfall events indirectly via loss of annual energy production.

To the best of our knowledge, we find a gap in existing literature for comprehensive models that encompass both stochastic spatial and temporal elements to describe the erosion process of the leading edge of wind turbine blades and the effects on their performance over long periods of degradation time horizons.

2.2 Diagnosing leading edge erosion

We here review state-of-the-art in leading edge erosion diagnostics and discuss potential approaches from recent work in probabilistic and machine learning research to solve the problem of spatio-temporal dependent diagnostics. The review is organized along two axes: (1) whether or not a forward model is known and to what extent it is used in training and testing and (2) whether or not the learning is supervised or unsupervised, i.e., whether or not the training relies on access to matched ground truth and measurement pairs.

Different approaches exist to diagnosing the extent of leading edge erosion on wind turbine blades. Traditionally, manual human inspection is used, although modern visual approaches are being developed to utilize drones paired with computer vision [19]. Visual inspection, however, requires the turbine to be shutdown and is highly dependent on weather conditions. Our aim is to use data-driven continuous monitoring methods to perform diagnostics without resorting to turbine shutdown. We review different machine learning and probabilistic approaches that have been put forth and which, given data recorded by sensors placed on the wind turbine (e.g. novel aerodynamic pressure sensors, SCADA, accelerometers, strain gauges, etc.), would be able to estimate the extent of leading edge erosion on wind turbine blades. In this context, the diagnostics task can be described as a multivariate time-series (MTS) classification/clustering problem; an algorithm is tasked with predicting the degradation status/class of a blade by analysing multiple time-dependent signals. We therefore include MTS methods, which have not been specifically applied to wind turbine blades in the past, allowing us to explore promising machine learning approaches from diverse fields unrelated to structural health monitoring: activity recognition, finance, anomaly detection, sound (speech, music) analysis, seismology, meteorology, human health signal (EEG and ECG) interpretation, etc. If the forward model of the degradation process is known, the diagnostics problem

becomes a supervised classification task, seeing that each MTS data point is associated with its degradation ground truth. Data-driven MTS classification is a field which is currently generating a lot of attention, with many promising methods that have been recently developed [20]. Within these approaches, we can differentiate between those that use the raw time-series data [21], known as end-to-end approaches, and those which first extract features that are then passed to a standard classification algorithm [22].

Extracting features from time-series data can be accomplished in many ways, with domain dependant feature engineering or statistical methods often being the first choices. Algorithms based on Empirical Mode Decomposition (EMD) are implemented for representing MTS as a superposition of simpler well-behaved components called Intrinsic Mode Functions (IMFs). EMD approaches are suitable for damage detection and degradation state recognition in the analysis of nonlinear and non-stationary signals. However, they have shown low performance in highly-stochastic signals with spike pulses and jumps [23,24]. Distance-based metrics, which evaluate the similarity between time-series data form another popular class of conventional feature construction methods [25]. Alternatively, bag-of-pattern models [26] [27] can also be used to generate features from sequential inputs. These methods work by dividing the time-series sample into subsequences that are then turned into an ensemble of discrete identifiers and finally a word count histogram, performed on the ensemble, is used to generate a feature vector. In [28] and [29], feature vectors are built from MTS data by passing the inputs through numerous random convolutional kernels. This approach, named ROCKET, has a relatively low computational cost, yet, when combined with a standard ridge classifier, it achieves state-of-the-art accuracy on the UCR time-series archive dataset [30]. Other methods turn the time-series inputs into feature images [31], which are then fed into Convolutional Neural Networks (CNNs) [32] designed for image classification, thus taking advantage of the recent advances in computer vision performance. Although feature engineering and feature extraction can potentially lead to accurate diagnostics with good explainability, we are interested in implementing end-to-end methods that use raw MTS data. This is due to the fact that feature-based methods often require large amounts of cumbersome human intervention, which limits generalization. Robustness is another potential downside, where changing the input, due to sensor malfunction for instance, might require re-selecting relevant features, while it can be factored into end-to-end approaches, provided it is part of the training data.

Conventional ('shallow') data-driven classification methods do not often use untransformed MTS as inputs, due to the difficulty associated with extracting relevant information from noisy, complex data. In contrast, deep learning methods often excel at learning hidden discriminative features, making them particularly well suited for end-to-end approaches [33]. CNNs have been applied to end-to-end MTS classification in the context of prognostic health management [34], surgeon skill classification [35] and other tasks [36]. CNNs are limited by their receptive field, making their use limited to relatively short time-series. Recurrent neural networks (RNNs) [37] are, by design, effective at solving tasks relating to sequential data. Long Short Term Memory (LSTM) Networks [38], currently the most commonly used type of RNNs, have been used to successfully classify clinical measurements [39] and action recognition tasks [40]. However, RNNs are also limited to relatively short input sequences due to memory requirements and are difficult to train. In recent years, Transformers [41] have attracted a lot of attention in the natural language processing community and have mostly replaced RNNs. These neural networks leverage the power of attention mechanisms to learn the relevant interdependencies within sequences. Transformers have increasingly been applied in other domains, such as computer vision [42], time-series forecasting [43], and multivariate time-series classification [44]. Graph Neural Networks [45], a class of deep data-driven methods which utilizes graph-structured data, have also been applied to end-to-end MTS classification [46]. This is done by first constructing an adjacency matrix

from the untransformed MTS data. In [47], spatio-temporal Graph Transformer Neural Networks (GTNN) are implemented in order to effectively capture both dynamic spatial and temporal trends. We could envisage using a GTNN model to leverage temporal and spatial correlations in the degrading sections of the three blades on a wind turbine.

As previously mentioned, deep end-to-end models are in general better suited for generalisation than feature-extraction approaches. Moreover, they can be further optimised for transferability [48], for instance by applying transfer learning methods, such as using domain adaption layers [49].

When the forward model of the degradation process is unknown, other methods for ground truth gathering must be considered, such as hand-labeling individual samples; a process which is often prohibitively time-consuming for large datasets. Instead, assuming that the labels are unknown, one can use unsupervised MTS clustering machine learning methods. In this type of approach, the data-driven algorithm learns to automatically cluster MTS samples into groups that exhibit similar degradation states [50]. Most MTS clustering methods are based on feature-extraction. However, it can be noted that in an unsupervised learning context, feature-extraction has a considerable impact on clustering performance [51], and it is therefore difficult to rely on standard domain-agnostic methods to construct features. In response to this difficulty, an emerging trend has been to learn the optimal feature representation of MTS data for clustering using neural networks [52], [44].

It is also worth mentioning unsupervised MTS anomaly detection methods [53], as these binary clustering approaches could be potentially extended to diagnostics. Anomaly detection for MTS is often based on similarity metrics [26,54,55], although these approaches are limited when it comes to capturing non-linearity and contextual anomalies (i.e. behavior that is abnormal only given the time at which it occurs). Neural networks have proven to be effective at detecting non-linear anomalies [56]. LSTMs were used to detect web traffic anomalies in [57], and [58] proposed the use of CNNs to detect abnormal behavior at multiple scales. General Adversarial Networks [59], a learning framework where two neural networks compete in a zero-sum game, have also been applied to anomaly detection [60]. Contrastive learning [61] is another approach to unsupervised clustering from multivariate time series signals for fault detection and diagnostics in the context of changing operating conditions and novel fault types. Franceschi *et al.* [52] showed the scalability of contrastive learning via triplet losses on long time series without labeling and without structural assumptions on non-temporal data. It is expected however that the performance of contrastive learning to suffer under highly stochastic input and operating conditions as is the case in wind turbines applications.

In the context of data-driven wind turbine blade condition monitoring, a number of methods have been reported in the literature [62]. In [63] vibrational frequency response functions were used as input features to neural networks, in order to detect changes in the structural health of a blade. LSTMs were trained to classify faults, based on multivariate sensor recordings of a model wind turbine test rig in [64], while [65] implemented a CNN to detect possible wind turbine blade breakages based on SCADA data. In [66], Support Vector Machines were trained on features built from active acoustic recordings, to diagnose healthy and damaged states of a model wind turbine. Another feature-extraction approach was combined with decision trees in [67] to diagnose different fault scenarios for model wind turbine. Finally, ice buildup on wind turbine blades was predicted with random forests trained on SCADA data in [68], while Weijtjens *et al.* [69] used Gaussian Processes trained on data emanating from low-cost tower-mounted sensors to do so.

Considering their extensive use in other domains, Transformers bear great potential for SHM damage detection. Some researchers have made use of attention mechanisms similar to those found in Transformers for bearing remaining useful life prediction [70], but to the best of the authors' knowledge, only in [71] have proper Transformer models been used in this context. In this work, however, an end-to-end approach is not used; instead, the model is fed a pre-processed input composed of time series features such as Mel Frequency Cepstral Coefficients (MFCCs) and Short Time Fourier Transformation. We choose Transformers as the base of our end-to-end approach for diagnostics. However, we implement additional modifications so as to be able to handle multivariate sequences on the order of several 10's of thousands of data points while still being able to track long term degradation progression, reflected by newly sampled sequences with possible discontinuities. Few, if any, of the existing MTS learning models discussed above are capable of this.

3 Modelling Erosion of the Leading Edge

3.1 Non-Homogeneous Compound Poisson Process

Leading edge erosion (LEE) is caused by environmental variations in the blade surface temperature oscillations, moisture, UV radiation, raindrops, sand, hailstones or other particles impacting the leading edge of the blade. It could also be initiated by surface cracks due to global strain from blade flexing [8], errors during manufacturing in terms of paint deposits, consistency of the gel coat thickness and bonding strength, or initiating surface damage during blade handling in transport or installation. This causes the surface material to be removed from the blade surface, leaving a rough profile that degrades the aerodynamic performance and, on the long term and if left untreated, impacts the structural integrity of the blade. Blade erosion may be more predominant in the sectional regions, where the local flow velocity is higher as this induces more energetic impacts with soiling or eroding elements. This is further exacerbated by the relatively greater impact the outboard region has on overall rotor performance. In addition, the Reynolds number and inflow turbulence influence the airfoil transition location and subsequently the aerodynamic performance of the wind turbine blades. As a result, it is not plausible to simulate all possible stages of LE erosion and uncertain inflow conditions; we therefore opt for a more pragmatic approach. Erosion initially initiates on the blades in the form of pits near the leading edge on the pressure side. These pits develop gradually over time into gouges, then steadily grow in their size and density to coalesce as delaminations. Gaudern [7] identifies five categories of severity based on proprietary inspection reports and photographs of Vestas turbines that have been operating for up to 5 years. In Sareen *et al.* [6] we find an analysis of the effect of erosion at the leading edge on the aerodynamic performance of the *DU96 – W – 180* airfoil, and categorized erosion from pits to delamination in different types and stages, as shown in Table 1. Each combination of type and stage of erosion has associated with it aerodynamic polar curves (C_L, C_D, C_M), derived via measurements in a wind tunnel [6,7,11]. Throughout the paper we adopt the labeling of the leading edge erosion severity shown in Table 2.

We propose a two-step empirical spatio-temporal stochastic model of LEE. Step 1 of the model includes a damage process that occurs at random times emulating the non-stationary time of arrival of degradation and its magnitude, with 10 discrete states (what we call erosion severity as shown in Table 2) based on Non-Homogeneous Compound Poisson Process (NHCPP) to describe the random degradation of the blade surface and implicitly its aerodynamic properties [6]. In step 2 of the model, the local leading edge degradation manifests by physical changes in the aerodynamic polars. This step

Table 1: Types and stages of leading edge erosion with the number of pits (P), number of gouges (G), and magnitude of leading edge delamination (DL) [6].

	Type A	Type B	Type C
Stage 1	100P	—	—
Stage 2	200P	200P/100G	—
Stage 3	400P	400P/200G	400P/200G/DL
Stage 4	—	800P/400G	800P/400G/DL+
Stage 5	—	—	1600P/800G/DL++

Table 2: Class labels adopted in this research for the severity categorization of leading edge erosion.

Severity class	Type & stage
0	Clean airfoil
1	Type A, Stage 1
2	Type A, Stage 2
3	Type A, Stage 3
4	Type B, Stage 2
5	Type B, Stage 3
6	Type B, Stage 4
7	Type C, Stage 3
8	Type C, Stage 4
9	Type C, Stage 5

generates an ensemble of stochastic aerodynamic polars for a given erosion severity of LEE in NHCPP by parameterizing the lift and drag coefficients curves [72].

The stochastic degradation process of a wind turbine blade LEE is given by a non-homogeneous Poisson process (NHCPP) over a finite time horizon. The NHCPP $\{N(t), t \geq 0\}$ has rate of arrivals $\lambda(t)$ on the time interval $t \in [0, T]$. A sample path of a NHCPP emulates two main properties in the proposed LEE: (1) random time of arrival, $0 \leq \tau_1 \leq \tau_2 \leq \dots$: these are the time instances corresponding to change in the degradation level of an airfoil aerodynamic properties (so-called shocks), and (2) magnitude of change $\{Y_n, n \geq 1\}$ in the degradation level of an airfoil aerodynamic properties at the n^{th} time of arrival. In practice, for a probabilistic assessment, many NHCPP paths are sampled. The model incorporates one or more zones (adjacent or disjoint) along the span of the blade(s) affected by erosion, but are assumed to undergo independent degradation processes. The NHCPP modify the definition of a Poisson process so that it can incorporate time-dependent rate. The non-homogeneous Poisson process is suitable given the fact that the rate of LEE is not constant in time (time-dependent arrival rates); on the short time scales (hourly), it is dependent on the rotor speed due to variations in the wind speed, while on the longer time scales it is dependent on seasonal variations such as rain intensity, and changes in environmental temperatures. We thus infer that the rate of occurrence of shocks is periodic, as shown in Figure 5. In addition, LEE consists of limited and finite number of stages resulting in varied and non-stationary incremental effects (severity) on the airfoils aerodynamic polars. It is in fact pragmatic to assume that the severity of LEE has a finite number of stages, because these could be categorised (e.g. via field observations), and their impact on aerodynamic properties emulated and quantified via measurements in wind tunnels as demonstrated in [6]. The impact of LEE on the lift and drag coefficients of the NACA64618 airfoil [11,14,73] for 10 severity classes is shown in Figures 3 and 4.

The non-homogeneous Poisson process is similar to an ordinary Poisson process, except that the average rate of arrivals per period $\lambda(t)$ is allowed to vary with time (Figure 5). A classic definition of the Non-Homogeneous Poisson Process is formulated

Figure 3. Lift coefficients for *NACA64618* for 10 severity classes of leading edge erosion.

Figure 4. Drag coefficients for *NACA64618* for 10 severity classes of leading edge erosion.

as follows [74]. Let $\lambda(t) : [0, \infty) \rightarrow [0, \infty)$ be an integrable function; the counting process $\{N(t), t \geq 0\}$ is called a non-homogeneous Poisson process with rate $\lambda(t)$ if all the following conditions hold:

1. $N(0) = 0$
2. $\forall t, s \geq 0$, and $0 \leq u \leq t$, $N_{t+s} - N_t$ is independent of N_u
3. $\forall t, s \geq 0$, $P(N_{t+s} - N_t = 0) = 1 - \lambda(t)s + o(s)$
4. $\forall t, s \geq 0$, $P(N_{t+s} - N_t = 1) = \lambda(t)s + o(s)$, and
5. $\forall t, s \geq 0$, $P(N_{t+s} - N_t \geq 2) = o(s)$

where, s is a very short interval of time. Here $o(s)$ is a function that is negligible compared to s , as $s \rightarrow 0$. Assuming $o(s) = g(s)$, then:

$$\lim_{s \rightarrow 0} \frac{g(s)}{s} = 0$$

One approach for generating Non-Homogeneous Poisson processes is the “process analogue” of acceptance-rejection called thinning, which is the scheme we adopt in our model. The procedure is as follows:

- 363 1. Choose λ_u such that $\lambda(t) \leq \lambda_u \forall t \in [0, T]$
- 364 2. Initialize $t = 0$ and $I = 0$
- 365 3. Generate $u_1 \sim U(0, 1)$
- 366 4. Set $t \leftarrow t - \frac{1}{\lambda_u} \log u_1$
- 367 5. If $t > T$, stop; Else go to next
- 368 6. Generate $u_2 \sim U(0, 1)$, independent of u_1
- 369 7. If $u_2 \leq \frac{\lambda(t)}{\lambda_u}$, set $I = I + 1$; $S(I) = t$
- 370 8. Go to Step 3

371 In the above procedure, the ratio $\frac{\lambda(t)}{\lambda_u}$ is the so-called *thinning probability*. In our
 372 model λ_u is chosen as the maximum of the rate function $\lambda(t)$ (e.g. see Figure 5). For long
 373 degradation periods, it might be necessary to break $[0, T]$ into small intervals and pick a
 374 λ_u for each interval in order to avoid a high rejection rate. This is known as piece-wise
 375 thinning. At the end of this procedure, the event times $S(I)$ (arrival times) and the
 376 counting process are yielded according to the Non-Homogeneous Process. Finally, for a
 377 non-homogeneous Poisson process with rate $\lambda(t)$, the number of arrivals in any interval
 378 is a Poisson random variable; however, its parameter can depend on the location of the
 379 interval. More specifically, we can write:

$$N(t+s) - N(t) \sim \text{Poisson}\left(\int_t^{t+s} \lambda(\alpha) d\alpha\right) \quad (1)$$

Figure 5. Cyclic rate function $\lambda(t)$ for the non-homogeneous Poisson process, representing the effect of weekly and seasonal variations on the rate. $\lambda(t)$ represents the rate of change in damage of LE erosion per given period.

380 Introducing the compounding effect to the Non-Homogeneous Poisson Process
 381 yields the so-called Non-Homogeneous Compound Poisson Process (NHCPP). The Com-
 382 pound Poisson Process, which is a very useful extension of a Poisson process, replaces
 383 the unit jumps of a Poisson process with random jump sizes [75]. The jumps magnitude
 384 at the n^{th} arrival time has value Y_n , $n \geq 1$ attached to it. The successive Y_n are assumed
 385 to be independent and identically distributed positive random variables each having
 386 the same distribution, and are also assumed independent of the underlying Poisson
 387 counting process of shocks. We assume that $\mathbf{Y} = (Y_1, Y_2, \dots)$ is a sequence of indepen-
 388 dent, identically distributed, real-valued random variables, and that $\mathbf{Y}$ is independent
 389 of the underlying Poisson process. The compound Poisson process associated with
 390 the given Poisson process $\{N(t), t \geq 0\}$ and the sequence $\mathbf{Y}$ is the stochastic process
 391 $\mathbf{Z} = \{Z_t, t \geq 0\}$, where:

$$Z_t = \sum_{n=1}^{N(t)} Y_n \quad (2)$$

392 The damage is always positive, i.e., that $P(Y_n \geq 0) = 1$, and the damage accumulates
 393 additively according to Z_t in Equation 2. In our model Z_t represents the cumulative

amount of erosion incurred on the blade section at time $N(t)$. In our model, we categorised 10 erosion severity levels reflected in the lift and drag coefficients, as shown in Figures 3-4 (other categorization could be specified as needed). The final level of degradation leads to the loss of function of the blade, not in the sense of a catastrophic loss (e.g. rupture), but rather implying that the blade loses its ability to generate lift efficiently. At this stage, we assume that once the blade section has reached level 9 of erosion, the process stops under the assumption that any further degradation becomes limited, since all the surface protective coatings and paint have already delaminated. We adopt a classical approach whereby $Y_1, Y_2, \dots, Y_n$ are each exponentially distributed according to density:

$$g_Y(y) = \mu \exp^{-\mu y} \quad (3)$$

where μ is the mean jump (shock) magnitude. It follows that the sum $Y_1 + Y_2 + \dots + Y_n$ is Gamma distributed $G^{(n)}(z)$. For details, we refer the interested reader to [76,77]. Formally, we adopt a truncated exponential distribution for Y_n in Equation 3. The logic being that large erosion magnitude jumps (e.g. large jumps in erosion severity) in one shock event are physically hard to justify. As a result, the upper truncation limit for the shock is set to a magnitude of 4 in our model. Furthermore, as more events arrive between $[0, T]$, and damage is compounded $Y_1 + Y_2, + \dots$, we adjust the upper truncation limit for the shock magnitude from 4 to 1 when $\{I \geq 3 \wedge (Z_{max} - \sum_{n=1}^{N(t)=I} Y_n) \leq 3\}$. Finally, sampled jumps of magnitude $Y_n > 0$ for $\tau_n < T$ are not allowed once the compounded damage has reached its highest compounded severity class ($Z_{max} = 9$) before the end of time horizon T has been reached. This is reasonable as any additional shocks (e.g. rain or hail) cannot incur any additional erosion, as there are not any more surface materials that can be easily eroded.

Finally, we introduce wind speed and blade location dependencies to the model. For a given time of arrival of a shock, our model associates higher damage (1) in the event when the shock is concurrent with higher inflow wind speeds due to higher momentum (and thus kinetic energy) of the impacting particles anywhere on the blade and (2) in the outboard sections of the blade due to the local higher relative speed of the flow. We require the mean jump (shock) magnitude μ to comprise a linearly increasing function of blade radial location and quadratic with wind speed. The final outcome is thus an NHCPP degradation paths as shown in Figure 6, where 5 zones along the span of blade 2 are chosen to undergo leading edge degradation. Even though the exact pattern and location of surface changes during operation is a random process, we see that our model tends to provide higher damage rates of the leading edge on the outboard sections of the blade compared to the inboard sections.

3.2 Stochastic aerodynamic Polars model

In this section, we generate a stochastic ensemble of degrading airfoil aerodynamic polars for use in forward aero-servo-elastic simulations. The outputs of the NHCPP are the degradation paths describing different degradation zones along the span of the rotor blades. Each arriving shock at a given time along these paths corresponds to a jump of a certain magnitude in the leading edge erosion severity. A jump in the erosion severity corresponds implicitly to a degradation of the aerodynamic properties of the airfoils affected by erosion along the span of the blade(s). However, uncertainties in the degrading airfoil aerodynamics lift and drag coefficients curves still remain to be accounted for. The stochastic aerodynamic Polars model, that we here describe, accounts for such uncertainties by parameterizing the lift and drag coefficients curves. Considerable effort and capital is invested in predicting the static aerodynamic lift C_L , drag C_D and moment C_M coefficients of airfoils as accurately as possible under various operating conditions. The lift and drag coefficients are then used by the wind turbine designers

Figure 6. A sample of the NHCPP of the leading edge erosion on 5 zones along the span of blade 2 over a 20-year period (240 months). Section 5 is the outermost section along the span of the blade.

as input to aero-servo-elastic simulations to predict power performance, extreme and fatigue loads in addition to stability margins in normal and extreme operating and stand still conditions. An airfoil's static aerodynamic data are almost exclusively derived from measurements acquired in wind tunnel tests. However, an airfoil section on the wind turbine rotor operates in 3-dimensional, un-steady and turbulent inflow under the guidance of a control system, none of which are accounted for in static wind tunnel tests. Some aspects of uncertainty in airfoil data (surface roughness, 3D corrections, effect of Re numbers, wind tunnel measurements or geometric distortions) have been studied in [72]. The general consensus is that uncertainties in airfoil data do affect a wind turbine's performance and structural loading. Consequently, our proposed LEE model also takes into account the inherent uncertainty in airfoil static lift and drag coefficients during the erosion period via a stochastic model of static airfoil lift and drag polar curves. The details of this model can be found in Abdallah *et al.* [72], with a short summary presented herein for conciseness.

A well known result from Blade Element Moment theory links the aerodynamic lift (C_L) and drag (C_D) coefficient to axial (a) and tangential (a') induction factors, as follows:

$$\begin{aligned} \frac{a}{1-a} &= \frac{\sigma' (C_L \cos \phi + C_D \sin \phi)}{4 \sin^2 \phi} \\ \frac{a'}{1-a} &= \frac{\sigma' (C_L \sin \phi - C_D \cos \phi)}{4 \lambda_r \sin^2 \phi} \end{aligned} \quad (4)$$

where σ' is the rotor solidity, Φ is the angle of the incoming relative wind with the rotor plane, $\lambda = \frac{\omega r}{V_0}$, ω is the rotor speed, r is the radial distance from the rotor center, and V_0 is the freestream wind. Our approach to affecting aerodynamic induction is by introducing a stochastic model of the lift and drag coefficients curves in BEM.

Several sources of uncertainties affect the lift and drag coefficients. These uncertainties associated with assessment of airfoil characteristics in wind tunnels, uncertainties due to 3D flow correction, uncertainties stemming from surface roughness, uncertainties related to the blade geometric distortions in manufacturing and handling, uncertainties related to the blade geometric distortions when deflected under load, uncertainties due to the effects of Reynolds number, uncertainties associated with extending airfoil

aerodynamic characteristics to post stall, and finally uncertainties stemming from the validation of airfoil data by field full scale prototype test. It is not possible to quantify the joint distribution of all these random variables and as a result a more simplified approach is chosen via a stochastic model as proposed in [72]. The stochastic model consists in parameterizing the lift coefficient curve by the slope in the linear range $\frac{\partial C_L}{\partial \alpha}$, the point indicating the start of the trailing edge separation ($AoA_{TES}, C_{L,TES}$), the point of maximum lift ($AoA_{max}, C_{L,max}$) and the point where the stall recovery is initiated ($AoA_{SR}, C_{L,SR}$). The drag coefficient is parameterized by a bias at low angles of attack, and by the point where max drag coefficient occurs at $AoA = \pm 90^\circ$ where it exhibits the largest variations. Figure 7 shows samples of the stochastic lift and drag coefficients for *NACA64618* for an erosion of severity class 5. These perturbations result in modified C_L and C_D curves that maintain the primary characteristics of the original curve, but differ in both magnitude and feature location, emulating possible uncertainties affecting the aerodynamic properties of the airfoil section under real operation.

Figure 7. Samples of the generated stochastic lift and drag coefficients of airfoil *NACA64618* corresponding to erosion severity class 5.

Putting it all together, the NHCPP coupled to the generator of stochastic ensemble of aerodynamic polars yields realistic degrading aerodynamic polars over the degradation time horizon, for every degrading zone and airfoil section on the rotor blades. For example, Figure 8 shows the degrading C_L over a 20-year period (240 months) for *NACA64618* airfoil. Figures 9-11 represent the corresponding degrading max lift coefficient, degrading angle of attack at max lift coefficient and degrading lift coefficient at $\alpha = 5^\circ$, respectively.

Figure 8. NHCPP generated degrading static C_L for NACA64618. This is used as input to the aeroelastic simulations for Blade 1, section 5. For each pre-selected degrading section on a blade a set of such curves are generated.

Figure 9. Degradation of the max lift coefficient for Blade 1, section 5.

3.3 Overview of the Algorithm

The main ingredients of the model include a (1) spatio-temporal stochastic damage process and (2) a generator of stochastic ensemble of degrading airfoil aerodynamic polars. The algorithm is summarized in Algorithm 1.

4 Uncertainty Modelling and Aeroelastic Simulations

Two categories of uncertain random variables (RV) are considered: wind inflow and aerodynamic effects. We have elaborated on the aerodynamic uncertainties in the

Figure 10. Degradation of angle of attack at max lift coefficient for Blade 1, section 5.

Figure 11. Degradation of the lift coefficient at $\alpha = 5^\circ$ for Blade 1, section 5.

497 previous section. In this section, we detail the wind inflow uncertainties and the aeroe-
 498 lastic simulations setup. The conventional wind turbine structural damage computation
 499 process utilizes aeroelastic load simulations for wind turbines under normal and extreme
 500 operation and wind inflow turbulence conditions, whereby the extreme and fatigue load
 501 cycles determined over a short period of time at each mean wind speed are extrapo-
 502 lated over the full expected lifetime. Such a process does not consider the changes in
 503 inflow and environmental changes over long time periods, indeed relevant to LE erosion
 504 process.

Algorithm 1: Spatio-temporal stochastic model of leading edge erosion.

Input : $\{CL, CD\}$: static lift and drag coefficients
Result: $\{CL'_{MC}, CD'_{MC}\}$: degrading lift and drag coefficients

- 1 Set the blades B_i affected by LE erosion: $B_i, i \in \{1, 2, 3\}$;
- 2 Set the eroding zones $EZ_{i,j}$ for B_i : $Z_{i,j}, j \in \{1, 2, 3, 4, 5\}$;
- 3 Set the erosion time horizon $[0, T]$;
- 4 Associate airfoils $A_{i,j,k}$ to erosion intensity range $N = [0, 9], k \in \{1, K\}$;
- 5 **for** $iter = 1, \dots, n$ **do**
- 6 Generate turbulent inflow samples for $[0, T]$: U, T_i, α, Ψ , and Σ ;
- 7 **foreach** blade B_i **do**
- 8 **foreach** Zone $EZ_{i,j}$ **do**
- 9 **foreach** Airfoil $A_{i,j,k}$ **do**
- 10 // NHCPP
- 11 **while** $t = 0, \dots, T$ **do**
- 12 do: sample arrival times $N(t)$;
- 13 do: sample erosion jumps Y_n ;
- 14 do: compound the erosion jumps, Z_t ;
- 15 // Inject smooth temporal transition
- 16 do: $[y_{trans}] = \text{GeneralizedLogisticFunction}(\cdot)$
- 17 **end**
- 18 // Generate stochastic airfoil data samples
- 19 **foreach** Erosion severity Z_t in a given NHCPP path **do**
- 20 do: Associate severity $Z_t \rightarrow \{CL, CD\}$ of $A_{i,j,k}$;
- 21 do: $[CL'_{MC}, CD'_{MC}] = \text{Generate_Stochastic_Aero_Data}(\cdot)$;
- 22 **end**
- 23 **end**
- 24 **end**
- 25 **end**

505 **4.1 Inflow RVs and their Stochastic Models**

506 The variation in the structural dynamic response of wind turbines is significantly
507 dependent on the turbulent inflow wind field conditions, including the mean wind speed,
508 turbulence, wind shear, and inflow skewness. In accounting for these influences, we
509 introduce the following RVs in the simulations setup: Mean wind speed, U , turbulence
510 intensity, T_i , wind shear, α , horizontal inflow skewness, Ψ , and the vertical inflow
511 skewness, Σ .

512 The mean wind speed follows a Weibull distribution $U \sim \mathcal{WB}\mathcal{L}(A_U, K_U)$, truncated
513 to $[4 - 25]$ m/s, with parameters specified as follows:

$$\mathbb{E}(U) = 8.5, \text{ where } A_U = \frac{2 \times \mathbb{E}(U)}{\sqrt{\pi}} \quad (5)$$

$$K_U = 2.0$$

514 The conditional dependence between the turbulence σ_U and the mean wind speed U is
515 defined in the Normal Turbulence Model described in the wind turbine design standard
516 [78]. Here, we elect to use a reference ambient turbulence intensity $I_{ref} = .16$ (the
517 expected value of the turbulence intensity at 15 m/s is called I_{ref}). This dependency is
518 given by the local statistical moments of $\sigma_u \sim \mathcal{LN}(\mu_{\sigma_u}, \sigma_{\sigma_u}^2)$ as:

$$\mathbb{E}(\sigma_u | U) = I_{ref}(0.75u + 3.8)$$

$$\mathbb{V}(\sigma_u | U) = (1.4I_{ref})^2 \quad (6)$$

519 As a result, the turbulence intensity is expressed as: $T_i = \frac{\sigma_u}{u}$.

520 The wind profile above ground level is expressed using the power law relationship,
521 which defines the mean wind speed u at height Z above ground as a function of the
522 mean wind speed u_h , measured at hub height Z_h as reference:

$$\frac{u}{u_h} = \left(\frac{Z}{Z_h} \right)^\alpha \quad (7)$$

523 where α is a constant called the shear exponent. The conditional dependence between
524 the wind shear exponent $\alpha \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2)$ and the mean wind speed U is given by [79]:

$$\begin{aligned} \mathbb{E}(\alpha | U) &= 0.088(\ln(u) - 1) \\ \mathbb{V}(\alpha | U) &= \left(\frac{1}{u} \right)^2 \end{aligned} \quad (8)$$

525 We define a custom conditional dependence between the inflow horizontal skew-
526 ness Ψ and the mean wind speed U , truncated to $[-11, 11]$ deg., $\Psi \sim \mathcal{N}(\mu_\Psi, \sigma_\Psi^2)$:

$$\begin{aligned} \mathbb{E}(\Psi | U) &= \ln(u) - 3 \\ \mathbb{V}(\Psi | U) &= \left(\frac{15}{u} \right)^2 \end{aligned} \quad (9)$$

527 The conditional dependence between the inflow vertical skewness Σ and the mean
528 wind speed U and turbulence intensity T_i , truncated to $[-6, 6]$ deg., is designed such as:

$$\Sigma \sim \mathcal{N}(\mu_\Sigma, \sigma_\Sigma^2) : \begin{cases} \mu_\Sigma = -2, \sigma_\Sigma^2 = 1.0, & \text{if } T_i \leq 10\% \text{ \& } \alpha \leq 0.1. \\ \mu_\Sigma = 1.5, \sigma_\Sigma^2 = 1.0, & \text{otherwise.} \end{cases} \quad (10)$$

529 The blade leading edge degradation scenario occurs over a 240-months period;
530 consequently, we introduce an additional element of uncertainty by allowing a time-
531 varying aspect of the inflow conditions, namely, the mean wind speed $\mathbb{E}(U)$, the shape
532 parameter K_U of the Weibull distribution, and the reference ambient turbulence intensity
533 I_{ref} as shown in the example in Figure 12.

534 We choose to sample the wind inflow and the aerodynamic RVs using the Sobol
535 Quasi-Random sequences, which are designed to generate samples that are uniformly
536 distributed over the unit hypercube, i.e., as uniformly as possible over the multi-
537 dimensional input space [80]. In total, we sample 1200 joint samples of the wind
538 inflow RVs over the degradation period, as shown in Figures 13 - 14. A sample of U ,
539 σ_U , α , Ψ and Σ is used to generate a realization of inflow turbulent wind field time
540 series, combined with a sample of stochastic and degrading C_L and C_D form the input to
541 the *OpenFAST* aero-servo-elastic environment to simulate the corresponding aeroelastic
542 response of the wind turbines structure under continuous erosion of the leading edge of
543 the blades.

544 4.2 Aero-servo-elastic Simulations Setup

545 Our coupled aero-servo-elastic simulations with the proposed NHCPP leading
546 edge degradation model setup is based on the *OpenFAST* simulator. *OpenFAST* [81],
547 is a coupled aero-hydro-servo-elastic analysis tool for modeling wind turbines. The

Figure 12. Long term inflow variations: (a) Varying mean wind speed and shape parameter K_U of the Weibull distribution. (b) Varying reference turbulence I_{ref} .

primary use of OpenFAST is to run nonlinear time-domain simulations. The simulations in OpenFAST considered the reference NREL three-bladed up-wind, horizontal-axis wind turbines with 126 m rotor diameter, 5 MW rated power and hub height of 90 m. The layout of the airfoils along the span of the blade are shown in Figure 15. We also list some of the more important properties of the simulated wind turbine in Table 3.

OpenFAST is a wind-turbine-specific nonlinear time-domain simulator that employs a combined modal and multibody dynamics formulation, adopting limited degrees of freedom (DOF). Large structural elements (blades and tower) are characterized by properties such as stiffness and mass per unit length, which account for flexibility characteristics. OpenFAST models the turbine dynamics using 24 degrees of freedom (DOFs), including two blade-flap modes and one blade-edge mode per blade, two fore-aft and two side-to-side tower bending modes, nacelle yaw, the generator azimuth angle and the compliance in the drive train between the generator and hub/rotor. The aerodynamic model is based on the unsteady Blade Element Momentum theory, including skew

Figure 13. Joint samples of the environmental sources of uncertainties for degradation period 0.
 $\mathbb{E}(U) = 8.5 \text{ m/s}, K_U = 2.0, I_{ref} = 0.09.$

Figure 14. Joint samples of the environmental sources of uncertainties for degradation period 5.
 $\mathbb{E}(U) = 9.0 \text{ m/s}, K_U = 1.95, I_{ref} = 0.12.$

562 inflow, dynamic stall and generalized dynamic wake. The Blade aerodynamic polars are
 563 provided as a-priori input and are used as lookup tables or for interpolation. In our case,
 564 the aerodynamic polars correspond to the degrading lift and drag coefficients generated
 565 in the NHCPP, such as the one shown in Figure 8. The stochastic input wind field
 566 uses the Kaimal turbulence model [82]. A common practice is to generate a significant
 567 number of stochastic simulations for various operating and environmental conditions
 568 in order to cover variability on aeroelastic fatigue and extreme load analysis due to the
 569 stochastic nature of the input wind field and variability in weather patterns over long
 570 time horizons (> 1 -year).

Figure 15. Distribution of airfoils along the span of the blade. Example of the NREL5MW reference wind turbine.

Table 3: Properties of the NREL 5-MW reference wind turbine.

Number of blades	3
Rotor diameter	126 m
Hub height	90 m
Rated power	5 MW
Cut-in wind speed	3 m/s
Cut-out wind speed	25 m/s
Control	Variable Speed, Collective Pitch
Variable speed	from cut-in to cut-out wind speed
Variable pitch	from cut-in to cut-out wind speed
Rated wind speed	11.4 m/s
Cut-in and rated RPM	6.9 – 12.1 RPM

571 In our simulation setup, we assign a maximum of 5 independent zones that could
 572 undergo leading edge erosion per blade. The location (normalized by the blade length)
 573 of the degradation zones along the span of the three blades are:

$$EZ : [0.65, 0.68], [0.70, 0.80], [0.82, 0.85], [0.87, 0.90], [0.92, 1.00]$$

574 We simulate 20 years (240 months) worth of wind turbine operation with blades LEE.
 575 We generate one sample every (approximately) six days, resulting in a total of 1200
 576 simulated samples. Every sample is a 600-second multi-variate time series with 228
 577 sensor signals each, sampled at 100Hz. Few examples of the time series signals are
 578 shown in Figures 16- 18.

Figure 16. Sample hub height wind speed. (Black) beginning and (Red) end of degradation period.

Figure 17. Sample lift coefficient at the airfoil profile corresponding to 95% of the span of blade 1. (Black) beginning and (Red) end of degradation period.

Figure 18. Sample flapwise bending moment at the root of blade 1. (Black) beginning and (Red) end of degradation period.

4.3 Retained Output from Aero-servo-elastic Simulations

As mentioned in the beginning of the paper, the motivation for this research is the Aerosense research project, where we are developing a novel MEMS-based aerodynamic surface pressure and aero-acoustic smart measurement system for wind turbines blades, for use in Structural Health Monitoring tasks. In this simulated setup, we assume one Aerosense node located at 0.96 of the blade length, located within eroding zone 5 (near the tip of the blade). From our aero-servo-elastic simulations, we elect to retain those output signals which are expected to emanate from the Aerosense measurements nodes, namely, lift and drag coefficients, angle of attack, and wind speed.

Table 4: Retained sensors output of aero-servo-elastic simulations.

Sensor name	Description
<i>Time</i>	Time steps of the simulations
<i>Wind1VelX</i>	X-direction wind velocity at hub-height
<i>B1N9Cl</i>	Lift force coefficient at Blade 1, Aerosense Node at 0.96R
<i>B1N9Cd</i>	Drag force coefficient at Blade 1, Aerosense Node at 0.96R
<i>B1N9Alpha</i>	Angle of attack at Blade 1, Aerosense Node at 0.96R

5 Diagnosing LEE via Transformers

The simulation pipeline described above allows us to generate data which replicate the sensory output of Aerosense nodes. Thus, we are able to produce datasets to train a deep learning method, with the end goal being to detect and estimate the extent of leading edge erosion on wind turbine blades. We choose to implement a modified version of a popular class of sequential deep learning models: Transformers [41].

594 To motivate the diagnostics task, we consider the case where C_L time series signals
 595 emanate from two sections along the span of the blade. Figure 19 shows a scatter plot
 596 of time series of C_L at sections 0.96R vs 0.75R of the blade for wind speeds varying
 597 between 6 – 16 m/s and no LEE (clean blade). Figure 20 shows a similar plot for a
 598 fixed wind speed 11 m/s and evolving severity of leading edge erosion at section 0.96R.
 599 An important property is that the relational dependency of the C_L between the two
 600 sections will change over time either due to changes in the severity of the leading edge
 601 erosion or due to short-term variation in inflow and operating conditions. The problem
 602 is thus to detect leading edge erosion and its severity, which could be regarded as a
 603 problem of finding the optimal discriminants for erosion versus other effects (inflow,
 604 operational conditions, aerodynamic uncertainties, etc.) from multivariate time-series
 605 response signals.

Figure 19. C_L for wind speeds varying between 6 – 16 m/s and no blade erosion.

Figure 20. C_L for fixed wind speed $U = 11$ m/s and evolving severity of leading edge erosion.

606 The following are aspects we wish to build into the diagnostics method for LEE
 607 classification, taking into account the nature/circumstance of an operating wind turbine
 608 in the field:

- 609 • Labeled data for LEE are hard to acquire and scarce; as a result, any method must
610 be designed not to suffer from overfitting under scarce labeled data availability.
- 611 • Diagnostics shall be done with remote streaming of sensor data. Human interven-
612 tion and turbine down-time should be alleviated.
- 613 • The data used in the diagnostics method shall replicate the sensory output of
614 a single micro-electro-mechanical-systems based aerodynamic and aero-acoustic
615 measurement node located near the tip of one wind turbine blade.
- 616 • The method shall be capable of ingesting 10 minute long multivariate time-series
617 (industry standard SCADA recording length), sampled at 100 Hz, resulting in
618 60'000 data points long sequences. A sampling rate of 100 Hz may seem excessive,
619 but the aim is to capture even small turbulence scales.
- 620 • Exploits a supervised pre-training scheme to initialize a Transformer-based network
621 by utilizing large-scale labeled data from aeroelastic simulations of the turbine and
622 a degradation model as presented earlier in the paper.
- 623 • Once pre-training is completed, the pre-trained model can be further adapted to
624 the specific classification task by fine-tuning the model parameters on small-scale
625 labeled data. In this way, the general knowledge and representations about LEE
626 can be transferred to a label-scarce task, thereby improving the generalization
627 performance of the model as well as reducing the risk of overfitting.
- 628 • Physics-constraints shall be built-in the loss or likelihood function.
- 629 • The output predictions should be probabilistic in nature.

630 5.1 Experiments and Datasets

631 We utilize multivariate time-series data generated via the coupled simulation
632 pipeline previously described. The term multivariate is used in the sense that we
633 are monitoring multiple signals pertaining to lift, drag, angle of attack and inflow ve-
634 locity emanating from an Aerosense node located at one section at the tip of the blade.
635 Multivariate could also be thought of in the sense that we can take advantage of the pres-
636 ence of multiple Aerosense stations at different locations along the span of the blade(s),
637 however, this is beyond the scope of the current work. After some initial testing, we
638 have opted to utilize the four variables shown in Table 4 as inputs to the Transformer.
639 For instance, no performance benefit was found when including simulated acceleration
640 data.

641 Three sets of experiments, each with different data requirements, are performed
642 aiming to answer the following questions:

- 643 1. *Are we able to learn the LEE severity classes from MTS data, in the general machine*
644 *learning sense, with balanced data classes and no prior knowledge?*
- 645 2. *In a continuous monitoring context, are we able to diagnose jumps in LEE severity and*
646 *therefore identify the degradation path that the system takes?*
- 647 3. *Are we able to do so in a realistic setting, with all previously described sources of uncertainty*
648 *present in the simulations?*

649 Thus, the goal of the first set of experimental tasks is to train the neural network
650 on a generalized dataset with reduced uncertainty and where each degradation class
651 appears in equal measure. This is not representative of a real degradation path, where
652 the inherent stochasticity of the NHCPP may result in some classes appearing very
653 briefly, but we aim to avoid biasing the network towards a random predominant class.
654 Moreover, this set of experiments also aims to understand how data availability affects
655 classification performance, and how separable the classes are. Two datasets, correspond-
656 ing to experiments 1.1 and 1.2, are generated: one with the full 10 severity classes and one

with a reduced amount of severities (levels 0, 1, 6 and 9). For this set of experiments, no information on previous states is used. In each of the sub-experiments, 4800 aero-elastic simulations are gathered, then split into train, validation and test sets in a 70/20/10 split.

The second set of experiments aims to assess whether using full degradation paths in a continuous monitoring setup to train the diagnostics method is a suitable strategy. Here, the datasets are comprised of full NHCPP degradation paths, albeit with reduced uncertainty. Due to the stochastic degradation, the datasets do not have balanced classes. Assuming that a continuous monitoring system is in place, we therefore have access to the previous degradation states. This allows for degradation monotonicity to be enforced in the prediction, thus constraining the output to physically possible solutions (i.e., it is physically impossible to have a state which is less degraded than previous states - except for the case of direct service intervention for repair and maintenance, which is out of scope in this work). Another objective is to evaluate whether severity grouping is a viable strategy. Indeed, grouping the LEE stages by type (see Table 1) could be beneficial as a coarse predictor, if it proves to be sufficiently accurate. Thus, in experiment 2.1, all 10 degradation levels are used as labels, while in experiment 2.2 the levels are grouped by type. Three full NHCPP degradation paths (new sample every 6 days, over a 20 year period) with 1200 simulations each are separated into training and validation sets in a 80/20 split. A full degradation path, with 1200 data points, is reserved as the test dataset for final evaluation.

The goal of the third set is to evaluate how the model would perform in a realistic continuous monitoring situation. Here, the dataset is also made of full NHCPP simulations, but in this case, all possible stochasticity is turned on. Again, we assume that we have access to the previous degradation states. We also evaluate class grouping, separating the experiment into two. Three full NHCPP degradation paths (new sample every 6 days, over a 20 year period), each consisting of 1200 MTS data points, are divided into training and validation sets based on a 80/20 split. The test dataset is comprised of one full degradation path, also with 1200 data points unused in training or validation.

Table 5 summarizes the differences between the datasets of the three sets of experiments, including the partition of data between the different subsets.

Table 5: Dataset properties of the different diagnostic experiments.

Parameter	Experiments					
	1.1	1.2	2.1	2.2	3.1	3.2
NHCPP severities	0-9	0, 1, 6, 9	0-9	0-9	0-9	0-9
Severity type grouping	-	-	-	0, A, B, C	-	0, A, B, C
Stochastic degradation	-	-	✓	✓	✓	✓
Inflow turbulence	✓	✓	✓	✓	✓	✓
Aerodynamic uncertainty	-	-	-	-	✓	✓
Weather variability	-	-	-	-	✓	✓
Num. training samples	3360	3360	2880	2880	2880	2880
Num. validation samples	960	960	720	720	720	720
Num. testing samples	480	480	1200	1200	1200	1200

5.2 Transformer Architecture

Here, we introduce the architecture of our Transformer neural network, used to classify long sequence multivariate time-series data and infer the degradation status of the leading edge.

Transformers are models that rely on self-attention mechanisms to highlight and learn dependencies within sequences. Typically, self-attention is implemented by parsing the input sequence into key (K), query (Q), and value (V) vectors. The attention weights on the values are then obtained by taking the scaled dot products of the query with all keys, and then by applying a softmax function. Using the classical notation [41], this writes:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (11)$$

where d_k is the dimension of the key and query vectors and is used to scale the dot product. In practice, h scaled dot-products are used in parallel, within Multi-Head attention layers. A Multi-Head model is able to attend jointly to information gathered from different parts of the input, providing an improvement in representation over a single attention mechanism. The final attention vector is obtained by concatenating each of the dot-product results:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (12)$$

with

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (13)$$

where the projections are parameter matrices $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $V_i \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{h \cdot d_v \times d_{\text{model}}}$.

Multi-Head attention layers are combined with fully connected networks and layer normalization to form the base architecture of each layer of the Transformer stack. We use a novel time-windowing Transformer model which is based on the patch system used in the Vision Transformer (ViT) model [42]. This architecture, as shown in Figure 21, aims to address the quadratic attention bottleneck, an obstacle which limits the length of sequences a Transformer can use. Indeed, the computational complexity of the self-attention layers in Transformer models scales as $\mathcal{O}(L^2)$, where L is length of the input sequence. Given our requirements, the input time-series have a length of $L = 60'000$, which is prohibitively resource intensive for standard Transformer models. To alleviate this issue, we propose to divide the data into N windows along the time-dimension, before passing each window through the learnable input embedding. This allows us to use the full input time-series without resorting to downsampling which would entail losing information.

Before dividing the MTS into windows, each of the individual channels/variables is normalized in time. Then, the input embedding encodes each time-series window into a vector of size d_{model} , which is the latent size used throughout the Transformer. The type of input embedding used has a considerable impact on performance and many embedding types can be envisaged. We choose to use a learnable linear embedding for simplicity, based on initial testing and the literature [42]. A class token is concatenated to the embedded sequence, such that its state at the output of the Transformer is used to infer the degradation severity. Class tokens are commonly used in natural language processing tasks [83], and are an effective way to retrieve categorical information from Transformers. Traditionally, positional encodings are then added to the sequence in order to instil directional information into the model. Contrary to standard NLP Transformer models, we do not use a positional encoding. Two positional encoding methods were

732 tested (classical sine functions and simple linear encoding), however, both of these
733 methods hindered classification performance.

734 The classification head consists of a single hidden layer Multilayer Perceptron
735 (MLP) that processes the class token at the output of the Transformer. It outputs a vector
736 with a size equal to the number of possible degradation classes, which, when passed
737 through a softmax activation, gives the likelihood scores of each class. For each class
738 output x_i , the softmax likelihood writes:

$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \quad (14)$$

739 If we aim to predict the degradation at multiple zone along the blade, we can
740 simply stack multiple MLPs, one for each zone. Table 6 summarizes the values used in
741 the Transformer architecture.

Table 6: Parameters of the Transformer architecture.

Number of windows, n	300
Window size, w	200
Internal Transformer dim., d_{model}	256
Transformer stack size, s	6
Num. self-attention heads, h	8
Self-attention head dim., d_{head}	64
Output MLP dim., d_{MLP}	2048

742 5.3 Loss functions

743 We first train and evaluate the Transformer model on the datasets with equal
744 amounts of degradation classes, in the sense of a traditional classification problem. Thus,
745 the objective function for this first task is the standard cross-entropy loss:

$$\mathcal{L}_{CE}(\mathbf{y}, \hat{\mathbf{y}}) = - \sum_{i=1}^n y_i \log(\hat{y}_i) \quad (15)$$

746 where $\mathbf{y}$ is a one-hot label vector indicating the correct class, $\hat{\mathbf{y}}$ is a vector containing the
747 predicted softmax probabilities for each class and n is the number of classes.

748 In the second and third set of experiments, it is assumed that the state of the system
749 is known for the previous sampling period. We use this information to enforce physical-
750 ity; we add a second term to the loss function that penalizes a predicted degradation
751 class that is lower than the known previous class. This second term is the margin ranking
752 loss:

$$\mathcal{L}_{MR}(\hat{c}, c_{prev}) = -\max(0, \hat{c} - c_{prev} + m) \quad (16)$$

753 where $\hat{c}$ is the predicted class, c_{prev} is the degradation class of the previous known state,
754 and m is the margin hyperparameter. Overall, the objective function for the second and
755 third experiments is therefore:

$$\mathcal{L}_{tot} = \mathcal{L}_{CE} + \alpha \mathcal{L}_{MR} \quad (17)$$

756 where α is a hyperparameter used to balance the two components.

Figure 21. Time-windowing architecture of the novel Transformer model. The input multivariate time-series is split along the time dimension into windows which are then individually passed through the learnable linear embedding. The learnable class token that is added to the sequence is used in the classification MLP head to predict the level of degradation.

5.4 Training regime

During training, we use a batch size of 20 along with the Adam optimizer [84] with parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$ and a learning rate of $lr = 5 \cdot 10^{-5}$ to perform stochastic gradient descent. After 40 epochs of training, the learning rate decays by a factor of 0.2.

To ensure that the trained model is able to generalize well, and does not overfit, dropout with a 0.3 rate is used in the attention, fully-connected and embedding layers. Furthermore, training and validation metrics (loss and accuracy) are monitored throughout the training sequence, allowing us to halt training without overfitting. Figure 22 shows the training curves of experiment 1.1, highlighting that training for around 60 epochs is sufficient in this case.

Figure 22. Training and validation accuracy for experiment 1.1 Beyond the 60th epoch no real gain in validation accuracy is made while training accuracy trends to 100%, which indicates overfitting.

6 Results

For each diagnostic experiment, a Transformer model is trained on the training dataset, monitored on the validation dataset and final evaluation takes place on the test dataset. All model hyperparameters are static throughout the experiments, only the number of training epochs varies, as we choose the epoch with the best validation performance. We report in the following sections the results for all three sets of experiments gathered on the previously un-seen test dataset.

6.1 Experiment set 1

The first set of experiments aims to assess the potential of the Transformer for diagnostics given ideal conditions: a balanced data set where each individual degradation class appears in equal measure. Table 7 reports the testing accuracy scores gathered for experiments 1.1 and 1.2. We note a significant difference between the results of the two experiments, where the 4 class setup outperforms the 10 class setup by 30% in terms of test accuracy. Knowing that Transformers are data-intensive models that respond well to large datasets, this discrepancy can be partly explained by accounting for the number of simulations per individual class. Indeed, as both training sets have the same total number of samples, there are 2.5 times the amount of samples per severity class in experiment 2.2. To factor out the disparity in the amount of data per class, we generate a large version of training dataset of task 1.1, with a total of 10176 training samples and 2544 validation samples. In this experiment (1.1 Large), the number of training samples per class is larger than for experiment 1.2 (1017 versus 840), yet the four class model still outperforms the 10 class model by over 16%. In general it is advantageous to train on larger amounts of severity classes from a risk management perspective, as it allows for more optimal maintenance intervention schemes. However, as highlighted above, a fine-grained approach requires more training data in order to diagnose accurately with high confidence and could result in higher amounts of false positives, which could then lead to an increase in Operation and Maintenance (O&M) costs. Thus, there is a trade-off between risk minimization via fine-grained diagnostics of LEE severity and increased costs due to higher amounts of false positives and requirements for larger training datasets, which can be optimized to meet risk management policies and budgetary specifications.

Table 7: Testing classification accuracy of experiments 1.1 and 1.2.

Experiment	Testing Accuracy [%]	
	All Predictions	>70% Likelihood
Exp. 1.1	66.67	72.65
Exp. 1.1 Large	80.63	85.56
Exp. 1.2	96.04	97.22

(a) Exp. 1.1: 10 levels of LEE severity.

(b) Exp. 1.2: 4 levels of LEE severity.

Figure 23. Confusion matrices of the predicted severity classes, evaluated on the test datasets of the first set of experiments.

The difference in accuracy can also be explained by the separability of the individual severity classes. We show in Figure 23 the confusion matrices generated on the test sets for experiments 1.1. and 1.2. It can be noted that the Transformer model is able to successfully differentiate between the lowest and highest of erosion severities, as demonstrated by the lack of misclassified samples with large differences in severity. Similar LEE erosion classes exhibit higher amounts of wrongly classified samples. This aligns with our expectations: small increases in the level of erosion only marginally increases the roughness of the leading edge, which has a minor impact on blade aerodynamics. It is therefore more challenging to distinguish between similar LEE severities based on integrated pressure quantities.

6.2 Experiment set 2

Here, we assess the use of stochastic degradation paths as diagnostic training points. Table 8 shows accuracy scores gathered on an un-seen degradation path for experiments 2.1 and 2.2. Figure 24 plots the predicted states of each MTS data point alongside the true degradation path, for the test dataset which contains a full NHCPP path with up to 10 possible LE severity classes. In addition, we show the prediction confidence of each model output based on its softmax likelihood. Figure 25 displays the median predicted severity using a three month rolling window.

These results show that this approach is viable and that we are able to successfully detect the jumps in degradation severity with some limitations. The main issue with training on stochastic degradation paths is the data imbalance. Indeed, the training dataset contains a majority of points belonging to classes 0, 8 and 9, while classes 5, 6 and 7 are underrepresented. This is reflected in the results, where the accuracy is high for class 0, but low for classes 5 and 6. Moreover, prediction confidence is in general lower

Table 8: Testing classification accuracy of experiments 2.1 and 2.2.

Experiment	Testing Accuracy [%]	
	All Predictions	>70% Likelihood
Exp. 2.1	65.42	78.41
Exp. 2.2	67.75	69.48

for underrepresented classes. A possible solution to address this is to train on grouped severity classes. We evaluate this approach in experiment 2.2 and plot the resulting predictions in Figures 26 and 27. Overall, this approach yields higher prediction accuracy, but it is still limited. Grouping artificially creates a somewhat balanced set and reduces class sparsity, however, it also leads to increased intra-class heterogeneity. As a result, learning to set the boundaries between the classes becomes more difficult and dependant on the number and the separability of the groups. This is reflected in the disparity of the minimum 70% confidence accuracy results between experiments 2.1 and 2.2. Indeed, the low intra-class heterogeneity of the 10 class approach results in low confidence predictions for ambiguous samples, while the same ambiguous samples are incorrectly classified with high a likelihood in the grouped approach due to the network accounting for high intra-class variance. There is a balance to be found between the accuracy gain and increase in intra-class heterogeneity induced by class grouping, depending on the number of groups. Should grouping be desired, unsupervised clustering approaches should be envisaged, in order to find the optimal number of groups.

In experiments 2.1 and 2.2, non-physical predictions are penalised via the additional loss term (see equation 16). The result of using this extra component is apparent in Figures 24 and 26: there are noticeably fewer misclassified points below the true degradation path than above it (11.5% vs 23.08% for experiment 2.1, 6.67% vs 25.58% for experiment 2.2).

Figure 24. Actual degradation path and predicted erosion severity classes for experiment 2.1. Only predictions with a likelihood greater than 70% are shown.

Figure 25. Actual degradation path and median predicted erosion severity classes for experiment 2.1 using a three month rolling window and upper rounding.

Figure 26. Actual degradation path and predicted erosion severity classes for experiment 2.2. Only predictions with a likelihood greater than 70% are shown.

Figure 27. Actual degradation path and median predicted erosion severity classes for experiment 2.2 using a three month rolling window and upper rounding.

6.3 Experiment set 3

In experiments 3.1 and 3.2, we assess how the diagnostics method performs on more uncertain degradation paths, with multiple sources of variability. Not only are there large class imbalances due to the stochastic degradation, but aerodynamic uncertainty (see Figure 7) and long-term weather fluctuations makes it challenging to distinguish between different LEE severities. Weather variability is not commonly used for long-term aero-elastic modelling in the wind energy industry, and is somewhat unrealistic, but the goal is to understand the limitations of the Transformer model by making inference extremely challenging. We report in Table 9 the accuracy scores gathered on an un-seen degradation path for experiments 3.1 and 3.2. Overall, classification accuracy is much lower than previous experiments, but using only high confidence predictions yields a larger boost in accuracy. This can be explained by the inherent stochasticity and the high intra-class variance of this dataset which makes high likelihood predictions rarer.

Table 9: Testing classification accuracy of experiments 3.1 and 3.2.

Experiment	Testing Accuracy [%]	
	All Predictions	>70% Likelihood
Exp. 3.1	35.00	45.75
Exp. 3.2	54.67	65.22

Figures 28 and 29 show how challenging this final task is, where we see many non-physical misclassified points and an overall low prediction confidence. Here, the data imbalance has a big impact on classification performance. As the training set does not contain any samples with a LEE severity class 9, the network is unable to predict this severity on the given test set. Given these harsh training conditions, it is unsurprising that performance is underwhelming. To mitigate this, class grouping by LEE type is again tested in experiment 3.2 (see Figures 30 and 31). Compared to experiment set 2, the benefit of grouping classes is clear here: performance is improved by almost 20%. This indicates that class grouping is a viable approach if intra-class heterogeneity is high by default and some classes are completely underrepresented. Nevertheless, even the results for grouped classes are lackluster, indicating that other strategies should be examined to deal with the very imbalanced datasets induced by the stochastic degradation paths. For instance, one could consider conditional retraining methods. By modifying the architecture so that it outputs confidence metrics based on how similar a sample is to the training set, as implemented in [85], one could then launch re-training procedures if multiple test samples that are very dissimilar to the training space are encountered.

Figure 28. Actual degradation path and predicted erosion severity classes for experiment 3.1. Only predictions with a likelihood greater than 70% are shown.

Figure 29. Actual degradation path and median predicted erosion severity classes for experiment 3.1 using a three month rolling window and upper rounding.

Figure 30. Actual degradation path and predicted erosion severity classes for experiment 3.2. Only predictions with a likelihood greater than 70% are shown.

Figure 31. Actual degradation path and median predicted erosion severity classes for experiment 3.2 using a three month rolling window and upper rounding.

6.4 Transferability and Curriculum Learning

Here, we evaluate the transferability of the different experiments, and assess the use of curriculum learning [86] as a method to improve accuracy on difficult results. In a curriculum learning training setup, the network is progressively exposed to harder datasets. In our implementation, we first train the model on the dataset from experiment 1.1, then progressively add the training data from experiments 2.1 and 3.1. The benefits of this approach should be twofold: (1) the data-intensive Transformer model is exposed to a larger dataset, and (2) the weights of the model are fine-tuned on more challenging samples, which helps to avoid local minima during gradient descent. Tables 10 and 11 show the results of the different transferability and curriculum learning experiments.

Table 10: Transferability and curriculum learning results.

Training Set(s)	Test Accuracy [%]		
	Set 1.1	Set 2.1	Set 3.1
Set 1.1	–	71.25	28.25
Set 2.1	65.00	–	29.42
Set 3.1	30.00	39.25	–
Set 1.1, then 2.1	77.71	83.50	20.33
Set 1.1, then 2.1 & 3.1	77.08	80.50	37.08

Table 11: Transferability and curriculum learning results, for high confidence predictions.

Training Set(s)	>70% Likelihood Test Accuracy [%]		
	Set 1.1	Set 2.1	Set 3.1
Set 1.1	–	80.21	30.19
Set 2.1	77.11	–	32.86
Set 3.1	35.58	40.97	–
Set 1.1, then 2.1	81.35	87.29	20.52
Set 1.1, then 2.1 & 3.1	84.42	88.53	50.22

We remark the following:

- The high accuracy of transferability tests between experiments 1.1 and 2.1 highlight the similarity of these datasets. Moreover, the balanced dataset of experiment 1.1 improves prediction quality for set 2.1.
- Although both sets 1.1 and 2.1 contain all degradation classes, networks trained on these sets do not transfer well to test set 3.1, undoubtedly due to the uncertainty included in this experiment.
- There is better transferability between sets 2.1 and 3.1, than between sets 1.1 and 3.1. This can be explained by the extra loss component which enforces monotonicity in the second and third sets of experiments.
- The first curriculum learning experiment (set 1.1 then 2.1) yields a large performance boost for test sets 1.1 and 2.1. This is to be expected due to the data-intensive nature of Transformers and the similarity between these sets.
- The first curriculum learning experiment reduces transferability to set 3.1. This is an indication of a loss of capacity to generalize to ambiguous data.
- The best test results on set 3.1 are obtained in the second curriculum learning experiment. This suggests that pretraining on sets with reduced stochasticity followed by fine-tuning on uncertain data is an effective approach.
- The second curriculum learning experiment yields the best high confidence accuracy for sets 1.1 and 2.1. Thus, adding difficult, stochastic data points of experiment 3.1 to the training dataset helps with regularization, enabling the model to construct a better internal representation of each severity class.

The curriculum learning test which includes the data from all experiments, leads to the highest high-confidence accuracy for the 2.1 test set. As this set is representative of a degradation path with standard aero-elastic simulation practices, we plot the results in Figures 32 and 33.

Figure 32. Results for test dataset 2.1 showing actual degradation path and predicted erosion severity classes for the curriculum learning experiment combining all datasets. Only predictions with a likelihood greater than 70% are shown.

Figure 33. Results for test dataset 2.1 showing actual degradation path and median predicted erosion severity classes for the curriculum learning experiment combining all datasets, using a three month rolling window and upper rounding.

7 Limitations and Discussion

All assumptions and modelling choices, constants, choice of probability distributions and their parameters in the proposed NHCPP model for leading edge erosion degradation could in principle be calibrated [87,88]. This, however, will prove very challenging given the data-scarce nature of measurements of erosion processes on operating wind turbines in the field over long time horizons. In addition, the impact of field data quantity and quality on model calibration and its implication on the generated NHCPP will need to be closely evaluated. One interesting extension to our NHCPP macro degradation model, is to further couple it to a micro model that describes the relative velocity between particles (including their density and size) and the blade, which leads to an expression for the mass flow of particles impinging the blade leading edge per unit of area [10]. Subsequently, a matricial expression for the number of particles impacting a unit surface is derived to describe the dependency of erosion severity from the atmospheric conditions at the site and the operational settings of the wind turbine.

Similar to the NHCPP, the Gamma process has also been traditionally used for modeling deterioration. A Gamma process has independent non-negative increments, but the shocks follow a Gamma distribution. While in a Poisson process there is a finite number of jumps in a finite time interval, in a Gamma process there are infinite numbers of jumps in a finite time interval. For this reason, the former are suitable for modelling usage such as damage due to sporadic shocks, whereas the Gamma processes are suitable for describing continuous ('graceful' - a succession of tiny increments), monotonic and gradual deterioration. The Gamma process can be regarded as a compound Poisson process of Gamma-distributed increments in which the Poisson rate tends to infinity and increment sizes tend to zero in proportion [89].

One of the main outcomes of the diagnostic experiments is the fact that the Transformer model is data-intensive. Indeed, our results point to the fact that more data almost always aids in classification performance. Furthermore, training on balanced datasets is always desirable, but obtaining these is difficult in real-life monitoring scenarios as it would require gathering data from many systems undergoing different degradation paths. To overcome this difficulty, the coupled NHCPP aeroleastic simulation setup can be used to replicate realistic degradation and produce balanced training sets which

can then be supplemented with real field data, in a similar manner to the curriculum learning experiments.

As mentioned in the literature review, feature-extraction learning methods are often preferred for MTS classification tasks owing to their higher precision. In this context, We tested the use of the state-of-the-art MINIROCKET method [29] with 10k kernels, combined with a standard linear classifier at the output for our diagnostics problem. This yielded an accuracy of only 55.21% on the test set of experiment 1.1 and 68.96% on the test set of experiment 1.2. This highlights the fact that very long sequences are challenging to deal with, while many methods found in the literature are not optimized for such tasks. Furthermore, feature extraction methods may encounter difficulty finding optimal features, due to the fact that this problem features a very slow degradation rate with no flagrant traits from one stochastic sample to another. On the contrary, Transformers are well suited for this kind of input, as the self-attention mechanisms are effective at filtering out unnecessary data while focusing on the parts of the signal that are important.

While the loss term added to penalize non-monotonicity of the degradation process does help to reduce non-physical predictions, it is not strictly enforced. Another option would be to enforce this condition in the softmax output layer. Although this method would most certainly improve accuracy, it would lead to error accumulation when implemented in the context of a continuous monitoring setup. With our approach erroneous predictions can be ignored by using a rolling window for instance. The proposed model could, however, be further improved by additional tuning of the objective function. One such improvement involves incorporation of an inflow-dependant multiplier that reduces the importance of samples that have highly unlikely inflow conditions. Furthermore, while the leading edge degradation process is inherently time-dependant, time was not factored into the final diagnostics approach. Initial tests which included a global time stamp in the model input, showed the Transformer overfitting to this variable. A probabilistic loss term that penalizes unlikely severities given the amount of operational time, could be a potential solution to this.

Another possible improvement could be the modification of the training procedure to a bi-directional procedure, similar to the BERT model [83]. In this approach, a pairwise input would be fed into the Transformer, and during the masked pre-training phase, the model would try to predict the class of either the first or second MTS at random. This could lead to a better representation of the data and allow the use of known reference states for comparative diagnostics.

Our proposed approach does not take positional information into account, yet, as shown in Figure 20, this may allow to more clearly distinguish the LEE severity classes along the span of the blade. Inserting positional information into our Transformer model can be achieved in different ways; one possible approach is to encode a graph structure in the Transformer architecture, as implemented in [90].

8 Conclusion

In this work we tackle the problem of leading edge erosion of wind turbine blades on a two-fold front. Firstly, we deal with the development of an appropriate model for simulation of such degradation processes and, secondly, we propose a monitoring-driven method for diagnostics of such damage processes. On the first front, we propose a stochastic spatio-temporal empirical model for modelling leading edge erosion degradation based on Non-Homogeneous Compound Poisson Process and couple this to the non-linear time marching OpenFast aeroelastic wind turbine computer simulator. The

coupled model is able to compute the aeroelastic non-stationary dynamic response of a wind turbine reflecting its behaviour under the effect of leading edge erosion, varying inflow conditions and aerodynamic uncertainties over a long period of degradation time horizon. On the diagnostic front, we adapt a deep neural network, namely a Transformer, to allow for use on very long sequence multivariate time-series. This allows us to solve the problem of spatio-temporal diagnostics of leading edge erosion on wind turbine blades, using the data emanating from the Non-Homogeneous Compound Poisson Process setup; a scheme that intends to emulate data recorded by aeroacoustic sensors placed on wind turbine blades. We showed that the diagnostics model effectively captures the temporal trends induced by long-term degradation of the leading edge. An attractive feature of this method is that it is well-suited for spatio-temporal degradation problems with a very long time horizon.

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