# A Review of Prognostics and Health Management in Wind Turbine Components

Jokin Cuesta[1], Urko Leturiondo[2], Yolanda Vidal[3], Francesc Pozo[4]

[1,2] *Artificial Intelligence and Data Area. Ikerlan Technology Research Center, Basque Research and Technology Alliance (BRTA). Pº J. Mª. Arizmendiarrieta, 2. 20500 Arrasate/Mondragón, Spain*
*jcuesta@ikerlan.es*
*uleturiondo@ikerlan.es*

[1,3,4] *Control, Data and Artificial Intelligence (CoDAlab), Department of Mathematics, Escola d'Enginyeria de Barcelona Est (EEBE), Campus Diagonal-Besòs (CDB), Universitat Politècnica de Catalunya (UPC), Eduard Maristany 16, 08019 Barcelona, Spain*
*yolanda.vidal@upc.edu*
*francesc.pozo@upc.edu*

[3,4] *Institute of Mathematics (IMTech), Universitat Politècnica de Catalunya (UPC), Pau Gargallo 14, 08028 Barcelona, Spain*

## Abstract

Wind turbines (WTs) play an essential role in renewable energy generation, and ensuring their reliable operation is essential for sustainable energy production and reduction of levelized cost of energy. In this context, the field of prognostics and health management (PHM) is a powerful tool to predict and assess the health status of WT components, thereby enabling timely maintenance and reducing downtime. The study begins with an overview of WT components studied, including the blades, gearbox, generator, and bearings, and their common failure modes. For each component, various remaining useful life (RUL) estimation methods are explored, categorizing them into physics-based, data-driven, and hybrid methods. Despite the potential benefits, the application of PHM strategies in WTs is currently limited. Although PHM strategies have been present for years, their development in WTs remains a challenge. These key challenges are presented, including uncertainty management, integrating physical knowledge into models, variable operational conditions, data issues and system complexity.

## 1. Introduction

To meet the European Commission's target of achieving climate neutrality by 2050, reducing the levelized cost of energy (LCOE) is vital. According to the International Renewable Energy Agency (IREA, 2023), operation and maintenance (O&M) costs, which include fixed and variable components, typically constitute between 10% and 30% of the LCOE for most wind industry projects as of 2022. This underscores the importance of optimizing maintenance activities for wind turbines (WTs). It involves the transition from traditional corrective and preventive maintenance approaches to predictive maintenance strategies, where maintenance tasks are scheduled based on the real-time and projected condition of components. In this context, the field of prognostics and health management (PHM), which covers various techniques to monitor the evolution of component wear, plays a critical role. Through PHM, it becomes possible to forecast remaining useful life (RUL) of components using historical and current operational data (Ferreira & Gonçalves, 2022).

To effectively implement PHM strategies for WTs, it is essential to explore their target components and their failure modes. The main components of a WT's drivetrain include the rotor, gearbox, and generator, which are interconnected via the low-speed shaft (LSS) and high-speed shaft (HSS) (see Figure 1). The gearbox, generator, and rotor blades are identified as the most critical subsystems, both onshore and offshore, based on downtime analysis (Dao, Kazemtabrizi, & Crabtree, 2019). Moreover, failures associated with the gearbox, rotor blades, and generator represent a higher expenditure, in that specified order (Tazi, Châtelet, & Bouzidi, 2017).

The main failure modes that affect these components are the

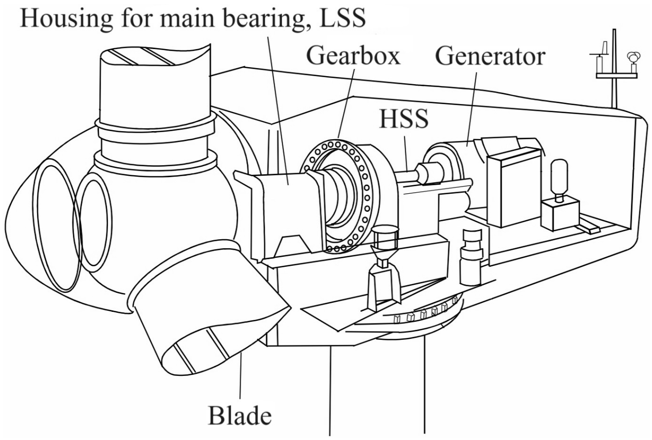



Figure 1. Schematic diagram of the components explored in this paper. Readapted from (Jiang et al., 2017).

following:

- **Blades**: fatigue, corrosion, and aerodynamic imbalance/ asymmetry (Catelani, Ciani, Galar, & Patrizi, 2020).
- **Gearbox**: abrasive wear, pitting, cracking, scuffing oil leakage, insufficient lubrication (Owolabi, Madushele, Adedeji, & Olatunji, 2023; Olabi et al., 2021).
- **Generator**: overspeed, overheat, wear, excessive vibration, rotor asymmetries, bar break, electrical problems (Olabi et al., 2021; Lydia & Edwin Prem Kumar, 2023).
- **Bearings**: axial cracking, spalling, pitting, brinelling (fretting) (Owolabi et al., 2023).

Based on the needs for PHM implentation in WT components, the scope of this review paper is to provide an in-depth analysis of the methodologies, algorithms, and techniques used to estimate the RUL of components within WT components. The aim of this review is to present works published from 2018 to March 25, 2024, thereby gathering recent advancements and trends in PHM specific to critical wind components, including blades, gearboxes, bearings, and generators. By addressing these challenges and providing a comprehensive review of the current state-of-the-art, this paper aims to contribute to a better understanding of the complexities and future research trends involved in developing RUL prognostics for wind turbines. The paper is structured as follows. Section 2 consolidates the research efforts made in the prediction of RUL classified by the component to which the techniques are applied; finally, Section 3 focuses on conclusions and key challenges.

## 2. Prognostics. RUL estimation

Prognostics refers to the examination of fault symptoms to forecast future conditions and RUL within designed parameters (ISO, 2012). This section aims to gather the works done for accurate prediction of RUL in WT components, classifying the methods into physics-based, data-driven and hybrid. The applications of components found coincide with the most critical components in terms of dowtime and repair costs mentioned above, classified in blades, gearbox, generator, other bearings (which include predictions of RUL of bearings whose location is not specified) and those that consider WT as a system. It is important to note that most of the works found focus on bearing prediction, many of them located on the HSS. These can be gearbox high-speed bearings, gearbox intermediate-speed bearings, and generator bearings (Z. Liu & Zhang, 2020). When the paper introduced specifies the location of these, they are included in the gearbox/generator subsection. If not, they are included in other bearings.

The distribution of eighty-one papers among years and components can be found in Figure 2. It can be seen that data-driven approaches are the most common ones to predict the RUL of WT components, and there is an increasing trend towards using hybrid models (Figure 2a). Furthermore, the components most studied have been the gearbox and the generator, respectively (Figure 2b). Figure 3 gathers all the methods found in the literature, classified by type and component.

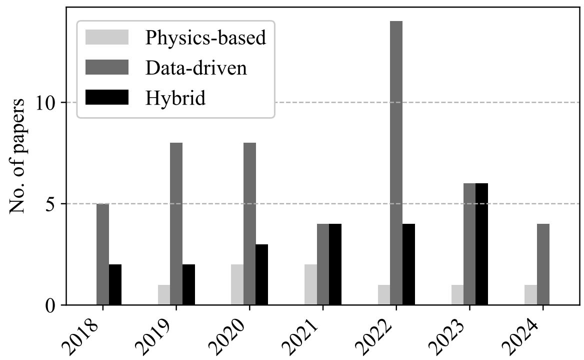
### 2.1. Blades

WT blades are engineered for a minimum of 20-year lifespan, resulting in load cycles between 10 millions and one billion, making them very susceptible to fatigue (Moroney & Verma, 2023). Twelve studies have been found to estimate the RUL of WT blades.

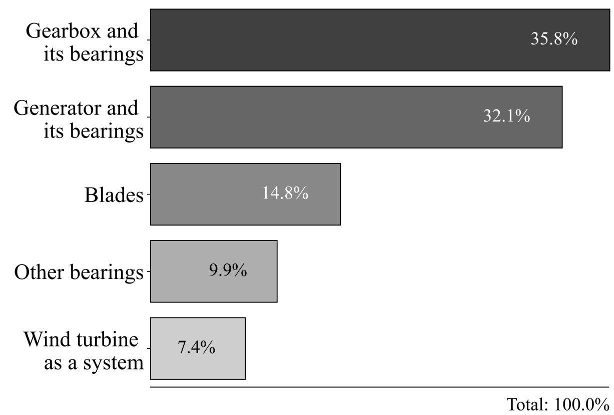
#### 2.1.1. Physics-based models

Physics-based models have been used for WT blades RUL estimation. Studies such as (Saathoff, Rosemeier, Kleinselbeck, & Rathmann, 2021) and (Moroney & Verma, 2023) employed aeroelastic load simulations, and durability and damage tolerance analysis (DADTA), respectively, to quantify the effects of factors like blade pitch misalignment, and material fatigue on RUL.

Furthermore, one of the most widely used physics-based techniques has been Kalman filtering. (Muto, Namura, Ukei, & Takeda, 2019) proposed a method that combines load monitoring with dynamic response estimation, enhancing the accuracy of RUL evaluation with Kalman filter (KF). (Boutrous, Puig, & Nejjari, 2022) introduced an innovative model-based prognostics procedure, leveraging zonotopic KFs to quantify uncertainties in degradation propagation. Moreover, (Vettori, Lorenzo, Peeters, Luczak, & Chatzi, 2023) presented an adaptive noise augmented KF approach, addressing challenges in noise calibration for joint input-state estimation. Their method demonstrated superior performance in virtual sensing (VS) applications in diverse structural scenarios.




(a) Number of papers found in this review, categorized by modeling approach (physics-based, data-driven, and hybrid), over the years.




(b) Percentage distribution of RUL prediction techniques found across WT components.

Figure 2. Classification of papers in this review: a) by year and type b) by component.

### 2.1.2. Data-driven models

Among data-driven methods that have been used to estimate the RUL of WT blades, particle filter (PF)-based approaches offer a dynamic and versatile solution. Studies conducted by (Valeti & Pakzad, 2018, 2019), (Jaramillo, Gutiérrez, Orchard, Guarini, & Astroza, 2022), and (Lee, Roh, & Park, 2022) demonstrated the efficacy of PF in accurately predicting RUL of blades under varying conditions, including fatigue damage and dynamic loading scenarios. Alternatively, various methodologies that employ data-driven strategies, particularly those using artificial intelligence (AI), presented different avenues. For instance, the work introduced by (Yue, Ping, & Lanxin, 2018), an end-to-end model based on convolutional neural network (CNN) combined with long short-term memory (LSTM) networks, exemplifies such approaches.

### 2.1.3. Hybrid models

Hybrid models offer promising results for an accurate prediction of the RUL of WT blades. (Rezamand et al., 2021a) introduced an integrated fuzzy-based failure prognosis method, leveraging recursive principal component analysis (PCA), a wavelet-based probability density function (PDF) estimation, a Takagi-Sugeno (T-S) fuzzy system, and a Bayesian algorithm. Their approach enabled real-time predictions by capturing blade failure dynamics, categorizing nonlinear degradation trends, and estimating RUL for each trend, culminating in an aggregated prediction for the entire system. Applied to supervisory control and data acquisition (SCADA) data from real wind farms, the methodology demonstrated robust performance, outperforming traditional Bayesian methods and effectively modeling nonlinear failure dynamics. In another study, (C. Peng, Chen, Zhou, Wang, & Tang, 2020) focused on improving the accuracy of icing failure prediction in WT blades through a novel balancing algorithm based on boundary division synthetic minority oversampling technology (BD-SMOTE) and a multi-step prediction process using multiple Elman neural networks (ENNs).

## 2.2. Gearbox

Gearboxes operate under harsh environmental conditions, including vibrations from turbine-side components and wind, as well as fluctuations from the load through the generator, while stepping up the speed from the LSS to meet the requirements of the HSS that drives the generator (Salameh, Cauet, Etien, Sakout, & Rambault, 2018). Their failures contribute to around 20% of WT downtime (Lydia & Edwin Prem Kumar, 2023); therefore, it is essential to accurately predict their RUL. Twenty-nine works have been identified.

### 2.2.1. Physics-based models

In the field of WT gearbox reliability estimation, only one work has been found in the literature. (Pagitsch, Jacobs, & Bosse, 2020) presented a pioneering approach for modeling WT gearboxes with minimal parameters, emphasizing its utility in estimating RUL and facilitating real-time condition monitoring (CM). The determination of forces and bending moments acting on the main components involves using information on non-torque loads from the rotor sub-model and rotor torque from the SCADA data record. These inputs are then employed to calculate inner loads on machine elements in the gearbox, using rigid beam models and analytical basic equations for a three-stage WT gearbox intermediate-speed shaft bearing forces. Finally, the modified life rating as defined in ISO 281:2007 is applied to predict RUL.

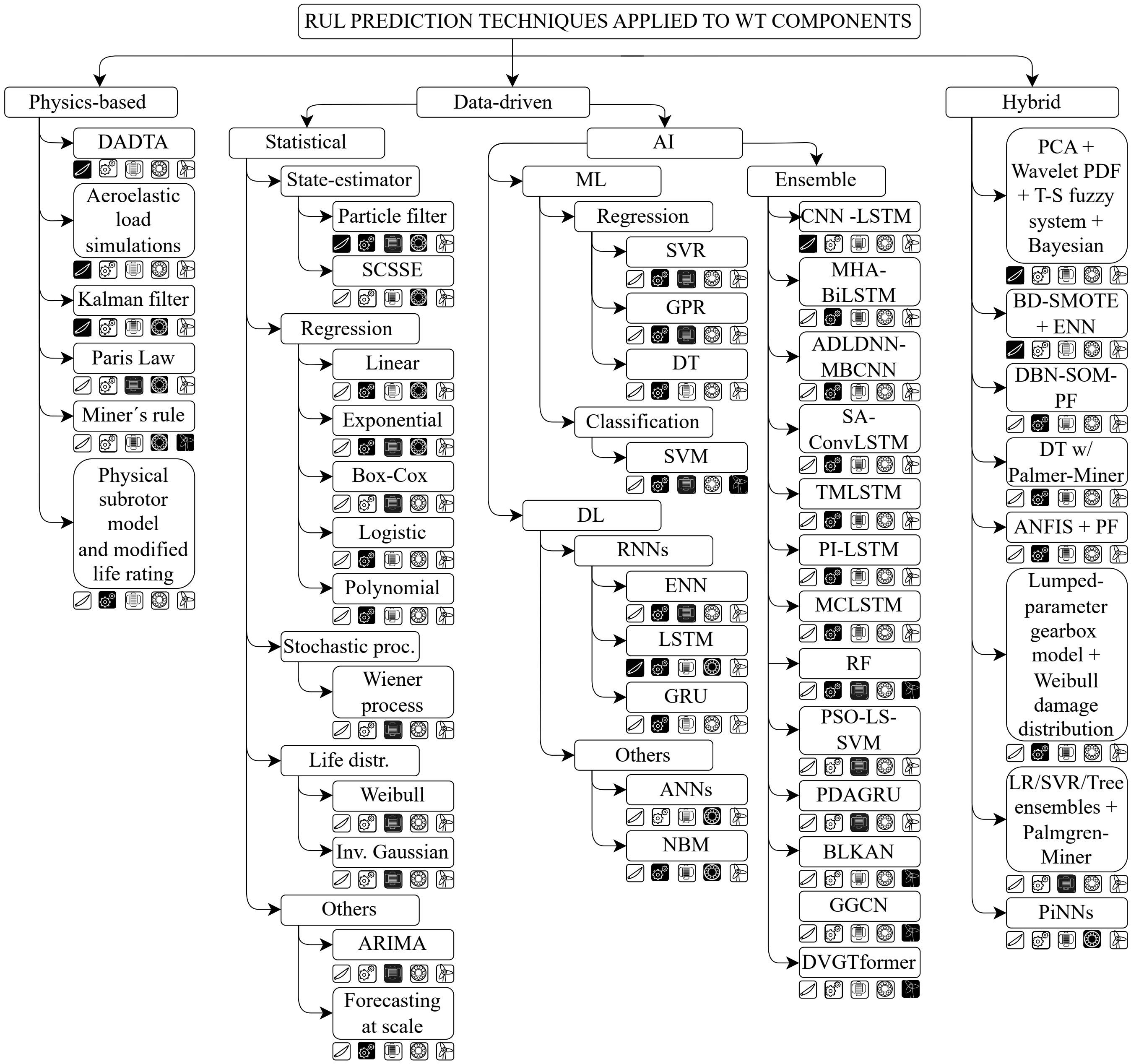



Figure 3. Techniques found in papers to predict RUL of WT components. The five categorical boxes correspond to, in order: blades, gearbox and its bearings, generator and its bearings, other bearings, and the WT as a system. The components highlighted with a black background represent those studied with the corresponding technique.

### 2.2.2. Data-driven models

Data-driven methodologies have gained attention to predict RUL of gearboxes. These approaches use advanced statistical methods, such as PF and regressions, and AI techniques such as advanced LSTM networks and artificial neural networks (ANNs).

Statistical PF methods have shown promising results. (J. Wang, Gao, Yuan, Fan, & Zhang, 2019) proposed an approach that integrates a PF with an expectation maximization algorithm, effectively predicting bearing defects from vibration signals in a 2MW WT gearbox. This method quantifies uncertainty in predictions, reduces false alarms, and highlights the importance of Bayesian inference for effective prognosis. (Cheng, Qu, Qiao, & Hao, 2019) introduced an enhanced particle filter (EPF) algorithm tailored for bearing RUL prediction in a 2.5 MW doubly fed induction generator (DFIG)-based WT gearbox. The EPF algorithm overcomes particle impoverishment issues, demonstrating superior performance compared to traditional PF methods. Additionally, (J. Wang, Liang, Zheng, Gao, & Zhang, 2020) proposed a Bayesian framework integrating fault prognosis and PF-based RUL estimation, effectively predicting RUL while quantifying uncertainties.

The construction of a robust health indicator (HI) is crucial for effective RUL prediction. Methodologies often combine signal processing and statistical modeling to extract information from sensor data. Then, the trend of these indexes is estimated using different algorithms. For instance, (Praveen, Shah, Pandey, Vamsi, & Sabareesh, 2019) developed a HI from vibration signatures using wavelet transform and PCA, achieving high RUL prediction accuracy with an exponential degradation model. On the other hand, (Lázaro, Yürüen, & Melero, 2020) constructed a SCADA-based functional indicator (FI) methodology using Gaussian mixture copula model (GMCM) from SCADA signals.

Several studies have explored AI methods to predict RUL of gearboxes in WTs. Some of them have compared various techniques to determine the most effective approach. For instance, (Tayade, Patil, Phalle, Kazi, & Powar, 2019) explored regression models, such as support vector regression (SVR) and random forest (RF) regression, augmented with PCA for feature selection, demonstrating the superior accuracy of RF over SVR in early fault detection and performance degradation prediction. (Carroll et al., 2019) employed ANNs, support vector machines (SVMs), and logistic regression to predict failures, with ANNs outperforming other methods in accuracy, especially when using SCADA and vibration data. (Elasha, Shanbr, Li, & Mba, 2019) focused on gearbox bearing prognosis, demonstrating the superiority of exponential and polynomial regression models over multilayer ANNs, particularly in terms of root-mean-square error (RMSE) and $R^2$ coefficient. Lastly, (Elforjani, 2020) conducted a comprehensive comparison of machine learning (ML) techniques, revealing that Gaussian process (GP) exhibited the lowest error levels compared to decision trees, SVM and a feedforward ANN.

Traditional LSTM networks have widely been used for time series forecasting; nevertheless, they show some limitations in RUL prediction. Several recent works have aimed to address these issues, recognizing the challenges posed by their inability to effectively capture global trends over time and tap into backward and forward connections within time series data. (Shen, Tang, Li, Tan, & Wu, 2022) introduced the multi-head attention bidirectional-long-short-term-memory (MHA-BiLSTM), which incorporates a multi-head attention mechanism to dynamically weigh circulating data between cells, thereby enhancing the network's ability to focus on information crucial to the degradation process. In another study, (Xiang, Qin, Liu, & Gryllias, 2022) proposed the automatic multi-differential learning deep neural network (ADLDNN), leveraging a measurement level division unit and a multi-branch convolutional neural network (MBCNN) to address the varying input contributions over time, demonstrating superior performance over existing methods. (Xiang, Qin, Luo, & Pu, 2022) proposed the spatio-temporally multidifferential network (SMDN), which used temporally multidifferential LSTM (TMLSTM) and spatially multidifferential CNN (SMCNN) sub-networks to capture spatio-temporal information effectively, achieving superior performance in RUL prediction. Furthermore, (Xiang, Qin, Luo, Wu, & Gryllias, 2023) presented the concise self-adapting deep learning network (CSDLN), which integrates a multi-branch 1D involution neural network (MINN) and a multi-head graph recurrent unit (GRU) to dynamically extract hidden features and adaptively learn them, resulting in enhanced RUL prediction accuracy. In addition, (B. Li, Tang, Deng, & Zhao, 2021) introduced the self-attention ConvLSTM (SA-ConvLSTM), which combines ConvLSTM architecture with a self-attention mechanism to selectively focus on important information and improve training efficiency and prediction accuracy. Moreover, (Z. Wang, Gao, & Chu, 2022) presented the pre-interaction LSTM, designed to enhance the capture of sequential features in time-series limited samples, especially during periods of interrupted continuous feature. Lastly, (Xiang, Li, Luo, & Qin, 2024) introduced the multi-cellular long short-term memory (MCLSTM) to obtain distinct distributions of monitoring data and utilized domain adversarial and active screen mechanisms for transfer learning.

Efforts have been made to select suitable features and construct a HI to enhance RUL estimation with AI. Qin et al. introduced the shape-characteristic similarity autoencoder (SM-SAE) network to automatically extract HI curves with specific shape characteristics from raw sensing data, thereby improving degradation trajectory characterization (Qin, Yang, Zhou, Pu, & Mao, 2023). Similarly, He et al. present the self-calibration temporal convolutional network (SCTCN) model, leveraging multidomain feature extraction and a self calibration module for improved prediction accuracy, even with limited time series data (He, Su, Tian, Yu, & Luo, 2022).

One of the important data sources for predictive maintenance in WTs is SCADA data. (Verma, Zappalá, Sheng, & Watson, 2022) extensively explored the use of high-frequency SCADA data, employing advanced techniques to address imbalanced operational regimes and enhance detection capabilities in WT gearbox failure prediction, and using ANN-based normal behaviour model (NBM) and one-class SVM. In contrast, (Bermúdez, Ortiz-Holguin, Tutivén, Vidal, & Benalcázar-Parra, 2022) present an ensemble neural network model, combining a two-dimensional CNN for spatial information extraction and an LSTM network for spatio-temporal feature analysis. The model was trained only on data from SCADA (Bermúdez et al., 2022).

#### 2.2.3. Hybrid models

Gearboxes have been the components to which most hybrid models found in this work have been applied. Desai et al. demonstrated the potential of integrating bearing-specific data from physics-based models with conventional SCADA data to enhance bearing failure prognostics (Desai, Guo, Sheng, Phillips, & Williams, 2020), highlighting significant improvements in F1 score and AUC. However, they suggested further refinement by developing individual models for each bearing type. Similarly, Mehlan et al. presented a VS method designed for online load monitoring and subsequent RUL assessment of WT gearbox bearings within a digital twin (DT) framework (Mehlan, Nejad, & Gao, 2022). The virtual sensor integrates data from readily available sensors in the condition monitoring system (CMS) and SCADA system with a physics-based gearbox model, employing multiple state estimation methods for load estimation and the Palmgren-Miner model for RUL assessment.

(Pan, Hong, Chen, & Wu, 2020) proposed a novel hybrid methodology which integrated deep belief network (DBN), self organizing feature maps (SOMs) and PF, DBN-SOM-PF. Their approach showcased superior performance in accurately predicting degradation tendencies and reducing RUL uncertainty. Moreover, (Cheng, Qu, & Qiao, 2018) introduced an adaptive neuro-fuzzy inference system (ANFIS)-based PF, demonstrating its superiority over traditional recurrent neural networks (RNNs). Their study addressed challenges in varying speed conditions through signal resampling, enhancing fault diagnosis effectiveness. (Qiao & Qu, 2018) also employed an ANFIS model in fault prognosis, showcasing accurate trend prediction validated by a gearbox run-to-failure test. Moreover, (Z. Li, Zhang, Kari, & Hu, 2021) proposed a comprehensive evaluation function combined with SOM network to construct a HI curve for gearbox-side high-speed shaft bearings (HSSB), then a Bayesian update model and expectation maximization algorithm were employed for RUL estimation. The model demonstrated superior accuracy in RUL prediction compared to SVR. Lastly, (Zheng et al., 2024) presented a multi-stage RUL prediction model tailored for WT planetary gearboxes, emphasizing interpretability and achieving promising results in real-world scenarios.

Finally, (Guo et al., 2020) integrated physics-domain models, SCADA data, and wind plant failure records to forecast the probability of failure for individual gearbox bearings. Focusing on bearing axial cracking, the study considers frictional energy accumulation and electrical power generation as prognostic metrics. The lumped-parameter gearbox model calculates gearbox bearing radial loads and displacements at any given torque, then Weibull distribution of the accumulated damage threshold of the accumulated energy is determined statistically.

### 2.3. Generator

Generators are labeled as critical components, as the O&M costs caused by the premature failure of the main components of WT generators can represent a significant portion –around 10-20%– of the overall energy expenses for a WT project (Cao et al., 2018). Twenty-six studies have been identified to predict the RUL of this component.

#### 2.3.1. Physics-based models

Within physics-based models to predict the RUL of WT generators, Kalman smoother (KS) method has been uniquely identified. (Saidi, Ali, Benbouzid, & Bechhofer, 2018) introduced an integrated prognostics methodology for WT HSSB prognosis, focusing on bearing failure prognosis driven by excessive shaft vibration. Their approach used a usage model based on Paris' law and a KS to estimate RUL, addressing inherent phase delay cancelation from Kalman filtering for improved accuracy and smoother estimated with confidence bounds.

#### 2.3.2. Data-driven models

In statistical methodologies, in both studies carried out by (P. Wang, Long, & Wang, 2020) and (Farhat, Chaari, Chiementin, Bolaers, & Haddar, 2022), the prediction of RUL for WT generator bearings is accomplished primarily through the implementation of exponential degradation models. Wang et al. used a fusion method based on PCA to construct a HI, which serves as a crucial metric reflecting the degradation level. This HI, alongside features extracted from vibration data and statistical analyzes such as monotonicity analysis and hierarchical clustering, contributes to accurate RUL estimation. Similarly, Farhat et al. also used an exponential degradation model for RUL prediction, initializing parameters based on healthy data and iteratively updating them as degradation progresses, obtaining a dynamic HI selection with good accuracy.

In their research, Rezamand et al. focused on reliability metrics for WT generators and real-time RUL prediction for critical bearings. In their study from 2019, (Rezamand, Carriveau, Ting, Davison, & Davis, 2019) explored reliability metrics using truncated WT generator data from a 100 MW wind farm, employing Weibull and accelerated life testing analysis to identify best-fitted distribution models and propose predictive PDF and hazard functions for the generator group. Subsequently, in their 2020 study, (Rezamand, Kordestani, Carriveau, Ting, & Saif, 2020) introduced a novel real-time Bayesian RUL prediction algorithm, incorporating comprehensive feature extraction, selection, and signal denoising techniques. It demonstrated superior performance over single-feature-driven Bayesian algorithms through experimental case studies, offering an improved approach to provide accurate RUL predictions by combining information from various single features using an ordered weighted averaging (OWA) operator.

The use of the Wiener process to predict RUL is apparent in several studies focusing on WT bearing health prognosis. (Hu et al., 2018) proposed an RUL prediction model based on the Wiener process and inverse Gaussian distribution, specifically targeting rear bearings of a 1.5 MW WT generator. By establishing an inverse Gaussian distribution function and deriving drift and diffusion parameters, the model effectively predicts RUL based on temperature monitoring data, offering valuable insights for maintenance decision-making. In a similar approach, (M. Liu, Dong, & Shi, 2023) addressed challenges associated with traditional vibration data by introducing a nonlinear Wiener degradation model integrated with physical and data knowledge. Their approach, which incorporates multi-sensor temperature data fusion and Bayesian analysis, demonstrated superior accuracy and reliability compared to conventional models. Furthermore, (Song, Youliang, Kai, Cheng, & Tao, 2020) employed both linear and nonlinear Wiener processes to construct dynamic monitoring and performance degradation models, intricately linking bearing temperature parameters, wind speed, and time. Lastly, (Lan et al., 2023) developed a precise RUL prediction method for WT generator bearings using a nonlinear Wiener process. Their approach used the $3\sigma$ criterion for online monitoring, considering a two-stage evolution of bearing performance parameters.

Other statistical techniques have been used to improve RUL prediction and health state estimation in WT systems. (Y. Peng, Bi, & Wang, 2023) developed a model integrating an enhanced two-phase Box–Cox transformation into the switching state-space model, capturing nonlinear degradation with phase transition behavior. Their adaptive parameter learning method dynamically estimated transformation parameters, phase transition positions, and predicted uncertainty. In a different approach, (Peter, Zappalá, Schamboeck, & Watson, 2022) proposed a framework combining data preprocessing, anomaly detection, and time series forecasting using SCADA signals and one-class SVM. Time series is then forecasted using an autoregressive integrated moving average (ARIMA) mode. Additionally, (Kramti, Saidi, Ali, Sayadi, & Bechhoeferer, 2019) leveraged PF-based Bayesian inference with advanced signal processing methods like spectral kurtosis and high order statistics for health state estimation of the generator-side HSSBs, demonstrating promising results for RUL estimation.

On the use of AI, Cao et al. have contributed significantly to the field of WT generator bearing RUL prediction with a series of innovative approaches. In their 2018 work, (Cao et al., 2018) introduced the interval whitenization Gaussian process (IWGP) method, which integrates interval whitenization and Gaussian process algorithms to forecast RUL under non-stationary operating conditions. This method showcased notable improvements over SVR and ANN techniques. Building upon this foundation, their subsequent study proposed a more comprehensive methodology, incorporating empirical mode decomposition (EMD) for signal denoising and fault development featuress (FDFs) extraction, followed by SVR modeling (Cao, Qian, & Pei, 2019). Expanding further, their latest work introduced the parallel gated recurrent unit with dual-stage attention mechanism (PDAGRU) model coupled with a novel uncertainty quantification method, enhancing both prediction accuracy and uncertainty assessment (Cao, Zhang, Meng, & Wang, 2023). By integrating a dual-stage attention mechanism and employing kernel density estimation and Monte Carlo dropout, their approach achieved remarkable RUL prediction accuracy.

The use of neural networks (NNs) in prognostics of HSSB in WT generators has shown promising results in recent studies. (Kramti, Ben Ali, Saidi, Sayadi, & Bechhoefer, 2018) introduced an ENN architecture, employing statistical time-domain features extracted from vibration signals as inputs. Their model demonstrated reliable performance even in the presence of noisy measurements. Expanding on this work, (Kramti et al., 2021) proposed a novel feature selection method based on monotonicity, trendability, and prognosability metrics, enhancing the robustness of their ENN-based prognostic model. Similarly, (Merainani, Laddada, Bechhoefer, Chikh, & Benazzouz, 2022) developed an ENN-based approach, incorporating a novel HI derived from spectral shape factor entropy and the Teager energy operator. Furthermore, (Hayder & Saidi, 2021) proposed a deep learning (DL)-based approach using a multilayer NNs, emphasizing the significance of kurtosis as a HI.

Authors also have contributed ensembled AI models to improve the accuracy of predictions. (Pandit & Xie, 2023) introduced an innovative approach combining sparrow search algorithm (SSA) with SVM, RF regression, and Gaussian process regression (GPR). Their model, driven by vibration signal analysis and feature selection based on monotonicity, exhibited high performance. In contrast, (Du, Jia, Yu, Shi, & Gong, 2023) addressed the limitations of traditional CNN models in extracting critical features for RUL prediction of bearings. They proposed a CNN prediction model enriched with a global attention mechanism (GAM) to enhance prediction accuracy. By transforming one-dimensional vibration signals into two-dimensional image data suitable for CNN processing and incorporating a HI constructed based on time-domain degradation characteristics, their approach significantly improved RUL prediction performance.

(Dameshghi & Refan, 2021) presented an innovative framework for prognosis, focusing on the failure behavior of the DFIG due to rotor electrical asymmetries. Their approach integrates the CMS module with the prognosis module, employing agents like the degradation trend index to enhance RUL prediction accuracy. Using a particle swarm optimization (PSO)-least squares (LS)-SVM method, with parameter tuning for LS-SVM optimization and a radial basis function (RBF) kernel. In a related study, (Kamarzarrin, Refan, Amiri, & Dameshghi, 2022) introduced a novel method for fault prognosis related to DFIG rotor winding, leveraging feature level fusion and adaptive thresholding based on process parameters. Their approach used classical time and frequency domain features to represent degradation behavior, with fault prognosis conducted using PSO-LS-SVM. Experimental validation, including simulated breakdown scenarios and comparisons with SVM- and NN-based approaches, showcases superior performance.

In their collective effort, the research group lead by Rezamand and Kordestani presented a comprehensive approach to predicting the RUL of WT generator bearings, addressing the challenges posed by varying operating conditions and uncertainty in prediction horizons. (Rezamand et al., 2021b) introduced a prognostic method integrating real-time SCADA data and vibration signals to assess the influence of environmental conditions on bearing failure dynamics, coupled with an adaptive Bayesian algorithm for RUL forecasting . In parallel, (Kordestani et al., 2022) proposed a feature extraction approach from vibration signals, followed by Bayesian RUL determination and high-level fusion methods such as the Hurwicz operator and Choquet integral to integrate RUL values and mitigate uncertainty.

### 2.3.3. Hybrid models

Only one work has been found aiming to predict RUL for WT generators with hybrid models, carried out by (Mehlan, Keller, & Nejad, 2023). A DT framework is introduced for the virtual sensing of WT hub loads. The research focuses on the estimation of aerodynamic hub loads, monitoring accumulated fatigue damage, and predicting the RUL of high-speed shaft generator side bearings. Using various data-driven regression models (linear regression (LR), SVR and tree ensembles) and a low-fidelity physics-based model, the bearing fatigue damage and RUL is based on ISO 281, which defines the equivalent dynamic load for cylindrical roller bearings. Then, long-term damage is obtained with Palmgren-Miner.

## 2.4. Other bearings

Eight works identified address the prediction of RUL of WT bearings that have not been previously listed, others have not been specified. All of them are included in this section. For instance, (Moynihan, Liberatore, Moaveni, & Khan, 2021) presented a physics-based approach to estimate RUL of main shaft bearings, employing strain measurements collected from blades and validated using real WT data, and fatigue life analysis is conducted using Miner's rule.

Within data-driven methods, (Jellali, Maatallah, & Ouni, 2022) proposed a method using temperature, viscosity, dynamic load, and fatigue damage for RUL prediction of WT main bearing, achieving high accuracy rates with a LR. The work of (Teng et al., 2020) emphasized a model-based approach using an improved unscented PF to study bearings located in the gearbox high-speed shaft, generator driven end, and generator non-driven end. This was done through measurement-centric methods, enhancing applicability for on-site WT scenarios. Moreover, (X. Li et al., 2023) built upon this foundation by introducing a method integrating degraded feature fusion models, threshold determination techniques, and self-constraint state-space estimator (SCSSE) to further enhance RUL prediction accuracy. (Encalada-Dávila, Puruncajas, Tutivén, & Vidal, 2021) developed an advanced prognostic approach, also ANN-based NBM, that relies solely on SCADA data to predict main bearing failure, enabling strategic maintenance scheduling several months in advance. Lastly, (Le, Lee, Dinh, & Park, 2024) compared similarity based model, employing an LSTM model, and degradation model, using LR and a stochastic exponential random model. The degradation models showed better performance. Lastly, (Bousebsi, Medoued, & Saidi, 2023) addressed RUL prediction for HSSB using the KS method. By incorporating Paris' Law and the KS, their method achieved enhanced accuracy in tracking degradation trends across five states.

Finally, (Yucesan & Viana, 2022) introduced the physics informed neural network (PiNN), a hybrid model for bearing fatigue damage accumulation. This was embedded as a RNN cell, where reduced-order physics models used for bearing fatigue damage accumulation, standardized bearing life formula found in ISO 281, and NNs represented grease degradation mechanism that quantifies grease damage that ultimately accelerates bearing fatigue.

## 2.5. Wind turbine as a system

Other six works have considered the drivetrain of a WT as a system. (Benmoussa, Djeziri, & Sanchez, 2020) proposed an integrated fault diagnosis and prognosis approach for WTs, employing a physics-based model, multi-class SVM classification, and a similarity-based method for RUL estimation without prior knowledge of degradation profiles. This method demonstrates effectiveness in handling uncertainties and transient operating modes, validated through a laboratory case study on a 750 kW WT. Similarly, (Binsbergen, Soares, Pedersen, & Nejad, 2022) developed a comprehensive physics- and SCADA-based model for RUL estimation in the WT drivetrain. By employing techniques such as load duration distribution and Miner's rule, their approach offers a holistic evaluation of the drivetrain's health and expected RUL.(de Souza Pereira Gomes et al., 2024) employed a RF model prediction, which sequentially conducts binary classification stages to determine if input samples represent conditions leading to a failure event within a specified time period.

In their series of works, (L. Wang, Cao, Xu, & Liu, 2022) proposed innovative methodologies aimed at improving RUL estimation within the drivetrain of WTs. First, they introduced the gated graph convolutional network (GGCN), focusing on multi-sensor signal fusion and precise RUL prediction. By leveraging spatial-temporal graphs constructed from multi-sensor signals, the GGCN effectively captured both temporal and spatial dependencies crucial for understanding degradation states. Furthermore, (L. Wang, Cao, Ye, & Xu, 2023) addressed the need for uncertainty quantification by incorporating a quantile regression layer, providing confidence interval estimated essential for maintenance planning. Building upon this foundation, their subsequent work introduced the Bayesian large-kernel attention network (BLKAN) to enhance RUL prediction and uncertainty quantification for bearings. The BLKAN balanced computational efficiency with long-range correlations and channel adaptability, employing Bayesian large-kernel convolutions and variational inference to infer probability distributions of model parameters. Finally, (L. Wang, Cao, Ye, Xu, & Yan, 2024) presented the dual-view graph Transformer (DVGTformer), which enhances RUL prediction accuracy by fusing information from multiple sensors to capture complex degradation patterns. By integrating temporal and spatial perspectives through cascading layers of a graph transformer, the DVGTformer achieved superior performance compared to existing state-of-the-art methods.

## 3. Conclusions and future directions

This review illustrates the dynamic field of RUL estimation for WT components, showcasing the evolution and diversity of methodologies and their respective challenges. The comprehensive analysis of eighty-one papers published since 2018 on RUL prediction models reveals a clear alignment with the identified critical subsystems and failure modes within WT systems in Section 1. The predominant focus on predicting the RUL of gearboxes (35.8%), generators (32.1%), blades (14.8%), and associated bearings aligns the findings from the downtime analysis and failure costs in the introduction, where these components emerged as the most critical.

Physics-based, data-driven, and hybrid models have been identified to achieve an effective prognosis, all gathered in Figure 3. When the underlying physics of the system is known, e.g., bearing fatigue analysis with Miner´s rule, physics-based methods offer interpretable results and accuracy without the need for large amounts of data. It is difficult, though, to obtain robust physics-based models of these complex systems. Data-driven methods, while requiring less physical knowledge, can effectively quantify prognosis uncertainty and process high dimensional data, though they may lack interpretability and generalize poorly with limited data, a common occurrence in many WT datasets, where data availability is often sparse or low quality. Hybrid methods combine the advantages of various approaches, but may face challenges in model selection and characterization of uncertainty. Figure 2a illustrates that data-driven methodologies are predominant in predicting the RUL of WT components, with a growing inclination towards hybrid models.

While the primary objective of these models is to improve the accuracy and robustness of their predecessors, significant barriers remain. The challenges outlined in our review of RUL estimation methods for wind turbine components were derived from an extensive analysis of existing literature and research findings. Through a systematic review process, recurring obstacles were identified and categorized into five distinct groups: inherent uncertainty management, integration of physical knowledge, consideration of variable operational conditions, data issues and complex system dynamics. This classification was based on the underlying nature of the challenges and their impact on prognostic accuracy and reliability. The distribution of papers that address these issues is shown in Figure 4 (one paper can address more than one challenge). These are discussed below.

1. **Uncertainty** from various sources, such as sensor noise and model variability, is a key obstacle. Thus, its quantification is essential to reduce the impact of uncertainties throughout maintenance optimization and decision-making. Techniques such as Bayesian belief networks (BBNs) and Monte Carlo methods aimed at minimizing it.
2. **Integration of physical knowledge**. The integration of underlying physics of the system is gaining attention to obtain higher accuracy and credibility of the prognosis, as shown in the hybrid methods subsections. However, there remains a need for further research and enhancement. Methods to integrate physical knowledge into NNs such as PiNNs offer promising avenues for accurate and interpretable prognostics (Chen, Ma, Zhao, Zhai, & Mao, 2022). In the industrial application facet, RUL prediction techniques have been applied to a number of important fields, including but not limited to aerospace systems, industrial robots, wind power systems, high-speed trains, etc. (H. Li, Zhang, Li, & Si, 2024), but there still remains a significant challenge in fully implementing these techniques within the components of WTs. However, there are some key limitations and challenges in model property aspects, which (Xu, Kohtz, Boakye, Gardoni, & Wang, 2023) summarized into five types: model selection, model structure, model parameter, model optimizer, and model prediction.
3. **Variable operational conditions**. WTs operate in dynamic environments characterized by fluctuating wind speeds, changing loads, and varying environmental con-

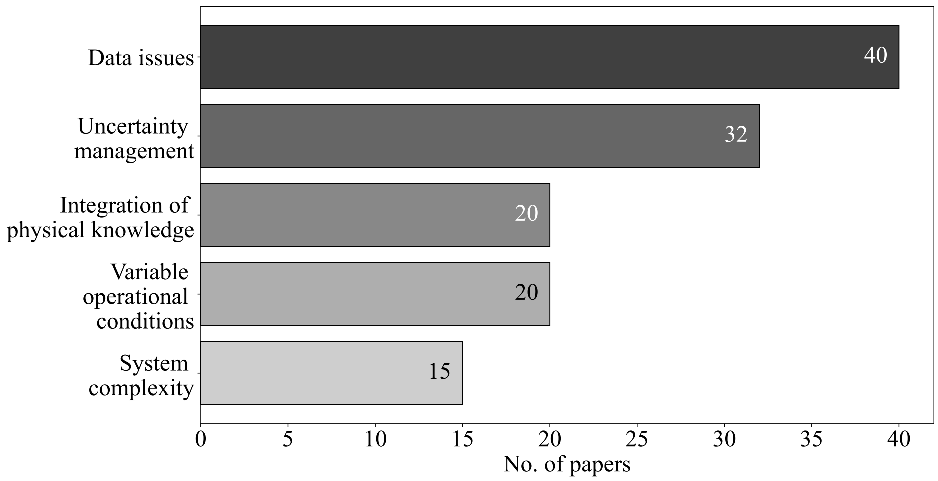



Figure 4. Amount of papers addressing challenges in WT component RUL prediction.

ditions. Such variability not only impacts the performance and wear of individual components, but also complicates the prediction of their future reliability and the accuracy of RUL models, often trained with similar operating conditions. The need for continuous online learning underscores the urgency for novel algorithms and hardware architectures (Elattar, El-Brawany, Elminir, Ibrahim, & Ramadan, 2023). In this context, transfer learning and domain adaptation present an opportunity to adapt models to varying operating conditions, although challenges remain to ensure prediction accuracy across different equipment (Ramezani et al., 2023). Therefore, the transferability assessment of different domains continues to pose a substantial challenge.

4. **Data issues**. Noisy measurements and a notorious lack of high-quality data are among these challenges. These difficulties are compounded by the scarcity of samples and monitoring data, which makes accurate predictive modeling even more challenging. Moreover, in many cases, only SCADA data are available, which presents a notable barrier, aggravated by the limited and low frequency samples, and the unbalanced nature of the condition data available for analysis. To overcome these obstacles, researchers must navigate the complexities of fusing multi-sensor signals to enrich the available data sources. Several papers within this study employ methodologies for multi-signal feature extraction and dimensionality reduction, such as PCA. However, it is beyond the scope of this review to delve into these techniques.

5. **System complexity**. WT are inherently complex systems, characterized by a multitude of interconnected components, as mentioned in the introduction. On one hand, multiple faults in a single component are a frequent occurrence, which are not considered in academic studies. On the other hand, the degradation process should take into account the way different components interact. To gain interpretability, more signal processing procedures could also be applied to the machine degradation process.

As research progresses, it is essential to address the identified challenges systematically, paying particular attention to the critical components within WT components. The implementation of PHM will facilitate the development of a robust predictive maintenance plan, which will contribute to the reduction of LCOE associated with O&M costs, thus aligning with the objectives of achieving green transition goals.

## Acknowledgment

This study was partially funded by the Spanish Agencia Estatal de Investigación (AEI) — Ministerio de Ciencia e Innovación, the Fondo Europeo de Desarrollo Regional (FEDER) through the research projects PID2021-122132OB-C21, PID 2021-122132OB-C22, and TED2021-129512B-I00; and by the Generalitat de Catalunya through the research project 2021-SGR-01044.

## References

Benmoussa, S., Djeziri, M. A., & Sanchez, R. (2020). Support vector machine classification of current data for fault diagnosis and similarity-based approach for failure prognosis in wind turbine systems. In M. Sayed-Mouchaweh (Ed.), *Artificial intelligence techniques for a scalable energy transition: Advanced methods, digital technologies, decision support tools, and applications* (pp. 157–182). Cham: Springer International Publishing.

Bermúdez, K., Ortiz-Holguin, E., Tutivén, C., Vidal, Y., & Benalcázar-Parra, C. (2022). Wind turbine main bearing failure prediction using a hybrid neural network. *Journal of Physics: Conference Series*, *2265*(3), 032090.

Binsbergen, D. V., Soares, M. N., Pedersen, E., & Nejad, A. R. (2022). A physics-, scada-based remaining useful life calculation approach for wind turbine drivetrains. *Journal of Physics: Conference Series*, *2265*(3), 032079.

Bousebsi, M., Medoued, A., & Saidi, L. (2023). Data-driven and physics-based approaches for wind turbine high-speed shaft bearing prognostics. In *Proceedings of 2023 international conference on control, automation and diagnosis (iccad)* (p. 1-6). IEEE.

Boutrous, K., Puig, V., & Nejjari, F. (2022). A set-based prognostics approach for wind turbine blade health monitoring. *IFAC-PapersOnLine*, *55*(6), 402-407.

Cao, L., Qian, Z., & Pei, Y. (2019). Remaining useful life prediction of wind turbine generator bearing based on emd with an indicator. In *Proceedings of prognostics and system health management conference, phm-chongqing* (p. 375-379). IEEE.

Cao, L., Qian, Z., Zareipour, H., Wood, D., Mollasalehi, E., Tian, S., & Pei, Y. (2018). Prediction of remaining useful life of wind turbine bearings under non-stationary operating conditions. *Energies*, *11*(12), 3318.

Cao, L., Zhang, H., Meng, Z., & Wang, X. (2023). A parallel gru with dual-stage attention mechanism model integrating uncertainty quantification for probabilistic rul prediction of wind turbine bearings. *Reliability Engineering and System Safety*, *235*, 109197.

Carroll, J., Koukoura, S., McDonald, A., Charalambous, A., Weiss, S., & McArthur, S. (2019). Wind turbine gearbox failure and remaining useful life prediction using machine learning techniques. *Wind Energy*, *22*(3), 360-375.

Catelani, M., Ciani, L., Galar, D., & Patrizi, G. (2020, 9). Optimizing maintenance policies for a yaw system using reliability-centered maintenance and data-driven condition monitoring. *IEEE Transactions on Instrumentation and Measurement*, *69*(9), 6241-6249.

Chen, X., Ma, M., Zhao, Z., Zhai, Z., & Mao, Z. (2022). Physics-informed deep neural network for bearing prognosis with multisensory signals. *Journal of Dynamics, Monitoring and Diagnostics*, *1*(4), 200-207.

Cheng, F., Qu, L., & Qiao, W. (2018). Fault prognosis and remaining useful life prediction of wind turbine gearboxes using current signal analysis. *IEEE Transactions on Sustainable Energy*, *9*(1), 157-167.

Cheng, F., Qu, L., Qiao, W., & Hao, L. (2019). Enhanced particle filtering for bearing remaining useful life prediction of wind turbine drivetrain gearboxes. *IEEE Transactions on Industrial Electronics*, *66*(6), 4738-4748.

Dameshghi, A., & Refan, M. H. (2021). Combination of condition monitoring and prognosis systems based on current measurement and pso-ls-svm method for wind turbine dfigs with rotor electrical asymmetry. *Energy Systems*, *12*(1), 203-232.

Dao, C., Kazemtabrizi, B., & Crabtree, C. (2019, 12). Wind turbine reliability data review and impacts on levelised cost of energy. *Wind Energy*, *22*, 1848-71.

Desai, A., Guo, Y., Sheng, S., Phillips, C., & Williams, L. (2020). Prognosis of wind turbine gearbox bearing failures using scada and modeled data. In *Annual conference of the phm society* (Vol. 12, p. 10).

de Souza Pereira Gomes, G., de Andrade Lopes, S. M., Araujo, D. C. P., Flauzino, R. A., Pinto, M. M., & Alves, M. E. G. (2024). Wind turbine remaining useful life prediction using small dataset and machine learning techniques. *Journal of Control, Automation and Electrical Systems*, *35*, 337-345.

Du, X., Jia, W., Yu, P., Shi, Y., & Gong, B. (2023). Rul prediction based on gam–cnn for rotating machinery. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *45*(3), 142.

Elasha, F., Shanbr, S., Li, X., & Mba, D. (2019). Prognosis of a wind turbine gearbox bearing using supervised machine learning. *Sensors*, *19*(14), 3092.

Elattar, H. M., El-Brawany, M. A., Elminir, H. K., Ibrahim, D. A., & Ramadan, E. (2023, Oct.). Artificial intelligence-based data-driven prognostics in industry: A survey. *Computers & Industrial Engineering*, *184*, 109605.

Elforjani, M. (2020). Diagnosis and prognosis of real world wind turbine gears. *Renewable Energy*, *147*(1), 1676-1693.

Encalada-Dávila, A., Puruncajas, B., Tutivén, C., & Vidal, Y. (2021). Wind turbine main bearing fault prognosis based solely on scada data. *Sensors*, *21*(6), 2228.

Farhat, M. H., Chaari, F., Chiementin, X., Bolaers, F., & Haddar, M. (2022). Dynamic remaining useful life estimation for a shaft bearings system. In F. Chaari, X. Chiementin, R. Zimroz, F. Bolaers, & M. Haddar (Eds.), *Smart monitoring of rotating machinery for industry 4.0* (p. 169-178). Cham: Springer International Publishing.

Ferreira, C., & Gonçalves, G. (2022, Apr.). Remaining useful life prediction and challenges: A literature review on the use of machine learning methods. *Journal of Manufacturing Systems*, *63*, 550-562.

Guo, Y., Sheng, S., Phillips, C., Keller, J., Veers, P., & Williams, L. (2020, July). A methodology for reliability assessment and prognosis of bearing axial cracking in wind turbine gearboxes. *Renewable and Sustainable Energy Reviews*, *127*, 109888.

Hayder, A. N., & Saidi, L. (2021). Applications of artificial neural networks with input and output degradation data for renewable energy systems fault prognosis. In *2021 12th international renewable energy congress (irec)* (p. 1-6).

He, K., Su, Z., Tian, X., Yu, H., & Luo, M. (2022, Jan.). Rul prediction of wind turbine gearbox bearings based on self-calibration temporal convolutional network. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1-12.

Hu, Y., Li, H., Shi, P., Chai, Z., Wang, K., Xie, X., & Chen, Z. (2018, Nov.). A prediction method for the real-time remaining useful life of wind turbine bearings based on the wiener process. *Renewable Energy*, *127*, 452-460.

IREA. (2023). *Renewable power generation costs 2022.*

ISO. (2012). *Condition monitoring and diagnostics of machines-vocabulary* (Tech. Rep. No. 13372:2012). International Organization for Standardization.

Jaramillo, F., Gutiérrez, J. M., Orchard, M., Guarini, M., & Astroza, R. (2022, July). A bayesian approach for fatigue damage diagnosis and prognosis of wind turbine blades. *Mechanical Systems and Signal Processing*, *174*, 109067.

Jellali, A., Maatallah, H., & Ouni, K. (2022). Predicting remaining useful life of wind turbine bearing using linear regression. In *2022 5th international conference on advanced systems and emergent technologies (ic_aset)* (p. 357-362).

Jiang, Z., Hu, W., Dong, W., Gao, Z., & Ren, Z. (2017). Structural reliability analysis of wind turbines: A review. *Energies*, *10*(12), 2099.

Kamarzarrin, M., Refan, M. H., Amiri, P., & Dameshghi, A. (2022). A new intelligent fault diagnosis and prognosis method for wind turbine doubly-fed induction generator. *Wind Engineering*, *46*(1), 308-340.

Kordestani, M., Rezamand, M., Orchard, M. E., Carriveau, R., Ting, D. S., Rueda, L., & Saif, M. (2022). New condition-based monitoring and fusion approaches with a bounded uncertainty for bearing lifetime prediction. *IEEE Sensors Journal*, *22*(9), 9078-9086.

Kramti, S. E., Ali, J. B., Saidi, L., Sayadi, M., Bouchouicha, M., & Bechhoefer, E. (2021). A neural network approach for improved bearing prognostics of wind turbine generators. *EPJ Applied Physics*, *93*(2), 20901.

Kramti, S. E., Ben Ali, J., Saidi, L., Sayadi, M., & Bechhoefer, E. (2018). Direct wind turbine drivetrain prognosis approach using elman neural network. In *2018 5th international conference on control, decision and information technologies (codit)* (p. 859-864).

Kramti, S. E., Saidi, L., Ali, J. B., Sayadi, M., & Bechhoeferer, E. (2019). Particle filter based approach for wind turbine high-speed shaft bearing health prognosis. In *2019 international conference on signal, control and communication (scc)* (p. 46-50).

Lan, X., Liang, D., Liu, W., Wang, Y., Han, Y., & Yu, Z. (2023). Remaining useful life prediction of wind turbine generator bearings based on nonlinear wiener process. In *Proceedings - 2023 3rd power system and green energy conference, psgec 2023* (p. 1124-1129). Institute of Electrical and Electronics Engineers Inc.

Le, T.-T., Lee, S.-J., Dinh, M.-C., & Park, M. (2024). Design of an improved remaining useful life prediction model based on vibration signals of wind turbine rotating components. *Energies*, *17*(1), 19.

Lee, I. Y., Roh, H. D., & Park, Y. B. (2022, Nov.). Prognostics and health management of composite structures under multiple impacts through electromechanical behavior and a particle filter. *Materials and Design*, *223*, 111143.

Li, B., Tang, B., Deng, L., & Zhao, M. (2021, June). Self-attention convlstm and its application in rul prediction of rolling bearings. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-11.

Li, H., Zhang, Z., Li, T., & Si, X. (2024). A review on physics-informed data-driven remaining useful life prediction: Challenges and opportunities. *Mechanical Systems and Signal Processing*, *209*(111120). doi: 10.1016/j.ymssp.2024.111120

Li, X., Teng, W., Peng, D., Ma, T., Wu, X., & Liu, Y. (2023, May). Feature fusion model based health indicator construction and self-constraint state-space estimator for remaining useful life prediction of bearings in wind turbines. *Reliability Engineering and System Safety*, *233*, 109124.

Li, Z., Zhang, X., Kari, T., & Hu, W. (2021). Health assessment and remaining useful life prediction of wind turbine high-speed shaft bearings. *Energies*, *14*(15), 4612.

Liu, M., Dong, Z., & Shi, H. (2023). Multi-sensor information fusion and multi-model fusion-based remaining useful life prediction of fan slewing bearings with the nonlinear wiener process. *Sustainability (Switzerland)*, *15*(15), 12010.

Liu, Z., & Zhang, L. (2020, Jan.). A review of failure modes, condition monitoring and fault diagnosis methods for large-scale wind turbine bearings. *Measurement: Journal of the International Measurement Confederation*, *149*, 107002.

Lydia, M., & Edwin Prem Kumar, G. (2023). 10 - condition monitoring in wind turbines: a review. In F. P. Garcia Marquez, M. Papaelias, & V. L. J. Junior (Eds.), *Non-destructive testing and condition monitoring techniques in wind energy* (p. 229-247). Academic Press.

Lázaro, R., Yürüen, N. Y., & Melero, J. J. (2020). Determining remaining lifetime of wind turbine gearbox using a health status indicator signal. *Journal of Physics: Conference Series*, *1618*(2), 022037.

Mehlan, F. C., Keller, J., & Nejad, A. R. (2023). Virtual sensing of wind turbine hub loads and drivetrain fatigue damage. *Forschung im Ingenieurwesen/Engineering Research*, *87*(1), 207-218.

Mehlan, F. C., Nejad, A. R., & Gao, Z. (2022). Digital twin based virtual sensor for online fatigue damage monitoring in offshore wind turbine drivetrains. *Journal of Offshore Mechanics and Arctic Engineering*, *144*(6), 060901.

Merainani, B., Laddada, S., Bechhoefer, E., Chikh, M. A. A., & Benazzouz, D. (2022). An integrated methodology for estimating the remaining useful life of high-speed wind turbine shaft bearings with limited samples. *Renewable Energy*, *182*, 1141-1151.

Moroney, P. D., & Verma, A. S. (2023). Durability and damage tolerance analysis approaches for wind turbine blade trailing edge life prediction: A technical review. *Energies*, *16*(24), 7934.

Moynihan, B., Liberatore, S., Moaveni, B., & Khan, U. (2021). Fatigue life analysis of main shaft bearings in wind turbines using strain measurements collected on blades. In (p. 185-192). Springer.

Muto, K., Namura, N., Ukei, Y., & Takeda, N. (2019). Model-based load estimation for wind turbine blade with kalman filter. In *2019 8th international conference on renewable energy research and applications (icrera)* (p. 191-199).

Olabi, A. G., Wilberforce, T., Elsaid, K., Sayed, E. T., Salameh, T., Abdelkareem, M. A., & Baroutaji, A. (2021, 9). *A review on failure modes of wind turbine components* (Vol. 14) (No. 17). MDPI AG.

Owolabi, O. I., Madushele, N., Adedeji, P. A., & Olatunji, O. O. (2023, 12). *Fem and ann approaches to wind turbine gearbox monitoring and diagnosis: a mini review* (Vol. 9) (No. 4). Springer Science and Business Media Deutschland GmbH.

Pagitsch, M., Jacobs, G., & Bosse, D. (2020). Remaining useful life determination for wind turbines. *Journal of Physics: Conference Series*, *1452*(1), 012052.

Pan, Y., Hong, R., Chen, J., & Wu, W. (2020, June). A hybrid dbn-som-pf-based prognostic approach of remaining useful life for wind turbine gearbox. *Renewable Energy*, *152*, 138-154.

Pandit, R., & Xie, W. (2023). Data-driven models for predicting remaining useful life of high-speed shaft bearings in wind turbines using vibration signal analysis and sparrow search algorithm. *Energy Science and Engineering*, *11*(1), 4557-4569.

Peng, C., Chen, Q., Zhou, X., Wang, S., & Tang, Z. (2020). Wind turbine blades icing failure prognosis based on balanced data and improved entropy. *Int. J. Sen. Netw.*, *34*(2), 126–135.

Peng, Y., Bi, R., & Wang, Y. (2023). Regime-switching model with adaptive adjustments for degradation prognosis. *IEEE Transactions on Instrumentation and Measurement*, *72*(6), 1-11.

Peter, R., Zappalá, D., Schamboeck, V., & Watson, S. J. (2022). Wind turbine generator prognostics using field scada data. *Journal of Physics: Conference Series*, *2265*(3), 032111.

Praveen, H. M., Shah, D., Pandey, K. D., Vamsi, I., & Sabareesh, G. R. (2019). Pca based health indicator for remaining useful life prediction of wind turbine gearbox. In *Vibroengineering procedia* (Vol. 29, p. 31-36). EXTRICA.

Qiao, W., & Qu, L. (2018). Prognostic condition monitoring for wind turbine drivetrains via generator current analysis. *Chinese Journal of Electrical Engineering*, *4*(3), 80-89.

Qin, Y., Yang, J., Zhou, J., Pu, H., & Mao, Y. (2023, Apr.). A new supervised multi-head self-attention autoencoder for health indicator construction and similarity-based machinery rul prediction. *Advanced Engineering Informatics*, *56*, 101973.

Ramezani, S. B., Cummins, L., Killen, B., Carley, R., Amirlatifi, A., Rahimi, S., … Bian, L. (2023). Scalability, explainability and performance of data-driven algorithms in predicting the remaining useful life: A comprehensive review. *IEEE Access*, *11*(4), 41741-41769.

Rezamand, M., Carriveau, R., Ting, D. S., Davison, M., & Davis, J. J. (2019). Aggregate reliability analysis of wind turbine generators. *IET Renewable Power Generation*, *13*(11), 1902-1910.

Rezamand, M., Kordestani, M., Carriveau, R., Ting, D. S., & Saif, M. (2020, Mar.). An integrated feature-based failure prognosis method for wind turbine bearings. *IEEE/ASME Transactions on Mechatronics*, *25*, 1468-1478.

Rezamand, M., Kordestani, M., Orchard, M., Carriveau, R., Ting, D., & Saif, M. (2021a). Condition monitoring and failure prognostic of wind turbine blades. In *2021 ieee international conference on systems, man, and cybernetics (smc)* (p. 1711-1718).

Rezamand, M., Kordestani, M., Orchard, M. E., Carriveau, R., Ting, D. S., & Saif, M. (2021b, Mar.). Improved remaining useful life estimation of wind turbine drivetrain bearings under varying operating conditions. *IEEE Transactions on Industrial Informatics*, *17*, 1742-1752.

Saathoff, M., Rosemeier, M., Kleinselbeck, T., & Rathmann, B. (2021). Effect of individual blade pitch angle misalignment on the remaining useful life of wind turbines. *Wind Energy Science*, *6*(5), 1079-1087.

Saidi, L., Ali, J. B., Benbouzid, M., & Bechhofer, E. (2018, Sep.). An integrated wind turbine failures prognostic approach implementing kalman smoother with confidence bounds. *Applied Acoustics*, *138*, 199-208.

Salameh, J. P., Cauet, S., Etien, E., Sakout, A., & Rambault, L. (2018, Oct.). Gearbox condition monitoring in wind turbines: A review. *Mechanical Systems and Signal Processing*, *111*, 251-264.

Shen, Y., Tang, B., Li, B., Tan, Q., & Wu, Y. (2022, Oct.). Remaining useful life prediction of rolling bearing based on multi-head attention embedded bi-lstm network. *Measurement: Journal of the International Measurement Confederation*, *202*, 111803.

Song, M., Youliang, S., Kai, J., Cheng, L., & Tao, W. (2020). Remaining life prediction of wind turbine bearing based on wiener process. *IOP Conference Series: Materials Science and Engineering*, *788*(1), 012089.

Tayade, A., Patil, S., Phalle, V., Kazi, F., & Powar, S. (2019). Remaining useful life (rul) prediction of bearing by using regression model and principal component analysis (pca) technique. In (Vol. 23, p. 30-36). EXTRICA.

Tazi, N., Châtelet, E., & Bouzidi, Y. (2017). Using a hybrid cost-fmea analysis for wind turbine reliability analysis. *Energies*, *10*, 276.

Teng, W., Han, C., Hu, Y., Cheng, X., Song, L., & Liu, Y. (2020, Mar.). A robust model-based approach for bearing remaining useful life prognosis in wind turbines. *IEEE Access*, *8*, 47133-47143.

Valeti, B., & Pakzad, S. N. (2018). Remaining useful life estimation of wind turbine blades under variable wind speed conditions using particle filters. In *Annual conference of the phm society* (Vol. 10).

Valeti, B., & Pakzad, S. N. (2019). Estimation of remaining useful life of a fatigue damaged wind turbine blade with particle filters. In S. Pakzad (Ed.), *Dynamics of civil structures, volume 2* (p. 319-328). Cham: Springer International Publishing.

Verma, A., Zappalá, D., Sheng, S., & Watson, S. J. (2022). Wind turbine gearbox fault prognosis using high-frequency scada data. *Journal of Physics: Conference Series*, *2265*(3), 032067.

Vettori, S., Lorenzo, E. D., Peeters, B., Luczak, M. M., & Chatzi, E. (2023, Feb.). An adaptive-noise augmented kalman filter approach for input-state estimation in structural dynamics. *Mechanical Systems and Signal Processing*, *184*, 109654.

Wang, J., Gao, R. X., Yuan, Z., Fan, Z., & Zhang, L. (2019). A joint particle filter and expectation maximization approach to machine condition prognosis. *Journal of Intelligent Manufacturing*, *30*(2), 605-621.

Wang, J., Liang, Y., Zheng, Y., Gao, R. X., & Zhang, F. (2020, Jan.). An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. *Renewable Energy*, *145*, 642-650.

Wang, L., Cao, H., Xu, H., & Liu, H. (2022). A gated graph convolutional network with multi-sensor signals for remaining useful life prediction. *Knowledge-Based Systems*, *252*, 109340.

Wang, L., Cao, H., Ye, Z., & Xu, H. (2023, Oct.). Bayesian large-kernel attention network for bearing remaining useful life prediction and uncertainty quantification. *Reliability Engineering and System Safety*, *238*, 109421.

Wang, L., Cao, H., Ye, Z., Xu, H., & Yan, J. (2024, Jan.). Dvgtformer: A dual-view graph transformer to fuse multi-sensor signals for remaining useful life prediction. *Mechanical Systems and Signal Processing*, *207*, 110935.

Wang, P., Long, Z., & Wang, G. (2020). A hybrid prognostics approach for estimating remaining useful life of wind turbine bearings. *Energy Reports*, *6*(9), 173-182.

Wang, Z., Gao, P., & Chu, X. (2022). Remaining useful life prediction of wind turbine gearbox bearings with limited samples based on prior knowledge and pi-lstm. *Sustainability (Switzerland)*, *14*(19), 12094.

Xiang, S., Li, P., Luo, J., & Qin, Y. (2024). Micro transfer learning mechanism for cross-domain equipment rul prediction. *IEEE Transactions on Automation Science and Engineering*, 1-11. doi: 10.1109/TASE.2024.3366288

Xiang, S., Qin, Y., Liu, F., & Gryllias, K. (2022, July). Automatic multi-differential deep learning and its application to machine remaining useful life prediction. *Reliability Engineering and System Safety*, *223*, 108531.

Xiang, S., Qin, Y., Luo, J., & Pu, H. (2022). Spatiotemporally multidifferential processing deep neural network and its application to equipment remaining useful life prediction. *IEEE Transactions on Industrial Informatics*, *18*(10), 7230-7239.

Xiang, S., Qin, Y., Luo, J., Wu, F., & Gryllias, K. (2023). A concise self-adapting deep learning network for machine remaining useful life prediction. *Mechanical Systems and Signal Processing*, *191*, 110187.

Xu, Y., Kohtz, S., Boakye, J., Gardoni, P., & Wang, P. (2023). Physics-informed machine learning for reliability and systems safety applications: State of the art and challenges. *Reliability Engineering and System Safety*, *230*(108900). doi: 10.1016/j.ress.2022.108900

Yucesan, Y. A., & Viana, F. A. (2022, May). A hybrid physics-informed neural network for main bearing fatigue prognosis under grease quality variation. *Mechanical Systems and Signal Processing*, *171*, 108875.

Yue, G., Ping, G., & Lanxin, L. (2018). An end-to-end model based on cnn-lstm for industrial fault diagnosis and prognosis. In *2018 international conference on network infrastructure and digital content (ic-nidc)* (p. 274-278).

Zheng, H., Deng, W., Song, W., Cheng, W., Cattani, P., & Villecco, F. (2024). Remaining useful life prediction of a planetary gearbox based on meta representation learning and adaptive fractional generalized pareto motion. *Fractal and Fractional*, *8*(1), 14.

## Biographies

**Jokin Cuesta** holds a degree in physics by the University of the Basque Country - Euskal Herriko Unibertsitatea (EHU-UPV, 2020). He furthered his education with a focus on data science master at Universitat Oberta de Catalunya (UOC, 2023) in Barcelona. He is currently engaged in the pursuit of an industrial PhD at the Artificial Intelligence and Data area in Ikerlan and the Control, Data, and Artificial Intelligence (CoDAlab) group in the Department of Mathematics at Universitat Politècnica de Catalunya. With a passion for the intersection of AI and CM, his research is dedicated to developing innovative methodologies for CM in the wind energy sector. His specific focus lies in identifying degradation patterns in WT components and estimating their RUL.

**Urko Leturiondo** is Industrial Engineer majored in Mechanics and Industrial Design by Tecnun - Engineering School of Universidad de Navarra (2012) and he received his PhD degree by Luleå University of Technology (2016). In 2012 he joined the Mechanical Engineering Department of Ikerlan as a PhD student, doing his research in collaboration with the Division of Operation and Maintenance Engineering of Luleå University of Technology. From 2016 to 2019 he worked as a researcher in the Control and Monitoring Area of Ikerlan. Since 2019 he has led different research teams in Ikerlan, being currently the DataOps team leader. His current research interests include condition monitoring, asset management, modelling of mechatronic systems, vibration and acoustic analysis, data analytics, artificial intelligence and DevOps.

**Yolanda Vidal** holds a degree in Mathematics (1999) and a PhD in Applied Mathematics (2005) from the Universitat Politècnica de Catalunya (UPC), Barcelona, Spain. As an Associate Professor at UPC and an IEEE Senior Member, she actively engages in multidisciplinary research. Her areas of expertise include condition monitoring, structural health monitoring, fault diagnosis and prognosis, predictive maintenance, machine/deep learning, mathematical modeling, and the application of these disciplines in WT technologies. She serves on the Editorial Board of several international journals, including Engineering Applications of AI (Elsevier), Wind Energy (Wiley), Wind Energy Science (Copernicus), Mathematics, Sensors, Energies, Frontiers in Built Environment, and Frontiers in Energy Research. Her prolific contributions are evidenced by more than 60 high-impact journal articles, 20 competitive R+D+I projects, 17 book chapters, 10 books, 3 supervised PhD theses, 1 invention patent, a collaboration contract with an industry partner, and over 110 conference papers.

**Francesc Pozo** obtained his degree in mathematics from the University of Barcelona in 2000, and his PhD in applied mathematics from the Universitat Politècnica de Catalunya (UPC) in 2005. Since 2000, he has been with the Department of Mathematics at UPC, where he is now a Full Professor and the coordinator of the Control, Data, and Artificial Intelligence research group. His expertise encompasses condition monitoring, control systems, data-driven modeling, identification, and structural health monitoring, with a special focus on WTs. He is an Editorial Board Member for several international journals, such as Structural Control and Health Monitoring, International Journal of Distributed Sensor Networks, Mathematical Problems in Engineering, Mathematics, Sensors, Algorithms, Journal of Vibration and Control, Frontiers in Built Environment, Frontiers in Energy Research, and Energies. His contributions to his field include over 70 high-impact journal articles, participation in 23 competitive R&D&I projects, authorship of 34 book chapters and 12 books, mentorship of 6 PhD candidates, the filing of 1 invention patent, a collaboration contract with an industry partner, and more than 130 conference papers.