electronics

Review

Prognostics and Health Management of Renewable Energy Systems: State of the Art Review, Challenges, and Trends †

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† This paper is an extended version of our paper published at the 2021 Annual Conference of the IEEE Industrial Electronics Society, Toronto, ON, Canada, 13–16 October 2021.

Abstract: The purpose of this study is to highlight approaches for predicting a system's future behavior and estimating its remaining useful life (RUL) to define an effective maintenance schedule. Indeed, prognosis and health management (PHM) strategies for renewable energy systems, with a focus on wind turbine generators, are given, as well as publications published in the recent ten years. As a result, some prognostic applications in renewable energy systems are emphasized, such as power converter devices, battery capacity degradation, and damage in wind turbine high-speed shaft bearings. The paper not only focuses on the methodologies adopted during the early research in the area of PHM but also investigates more current challenges and trends in this domain

Keywords: data acquisition; health indicator; machine learning; power converter; prognostics and health management; prognostic approach; remaining useful life prediction; wind turbine generators

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Citation: Saidi, L.; Benbouzid, M. Prognostics and Health Management of Renewable Energy Systems: State of the Art Review, Challenges, and Trends. *Electronics* **2021**, *10*, 2732. https://doi.org/10.3390/electronics10222732

Academic Editors: Jianguo Zhu, Gianpaolo Vitale and Shen Yin

Received: 6 October 2021
Accepted: 2 November 2021
Published: 9 November 2021

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1. Introduction

RAMS (reliability, availability, maintainability, and safety) services are now widely applied in industrial applications to perform in-depth assessments and interventions. As a result, industrial maintenance is proving to be one of the goals of industrial revolutions and research in this field, which translates into "industry-research" alliances or even major projects, such as the IMS (intelligent maintenance systems) center [1–4].

The detection and diagnosis of faults are critical in the industrial world [5]. Indeed, they help to improve availability, productivity, and the safety of people and equipment by detecting problems quickly and early. New industrial constraints are gradually affecting traditional ways for monitoring the health state of industrial equipment, such as preventative and corrective maintenance [2,4–6].

The "modern" and smart industries, which integrate physical manufacturing and operations with smart digital technologies, machine learning, big data, and cloud computing, have adopted a variety of advanced and sophisticated and signal processing and machine learning techniques to fulfill their needs. These traditional measures (preventive and corrective maintenance) are strengthened by proactive actions of degrading events on an industrial scale [1–6].

Figure 1 reports the main components of a horizontal wind turbine and their corresponding fault. A good classification of electromechanical system faults and their diagnosis methods is given in [7]. Several innovative signal processing and machine learning approaches have been developed. Manufacturers are working to improve their capacity to forecast failures before they happen, as well as to prepare the appropriate preventative procedures as fairly and quickly as feasible (maintenance planning and scheduling). In addition, the use of PHM solutions to improve a product's effective reliability and availability throughout its life cycle is gradually becoming more important, and the PHM process is now critical in Industry 4.0 or smart industry, for many reasons, as detailed in [3].

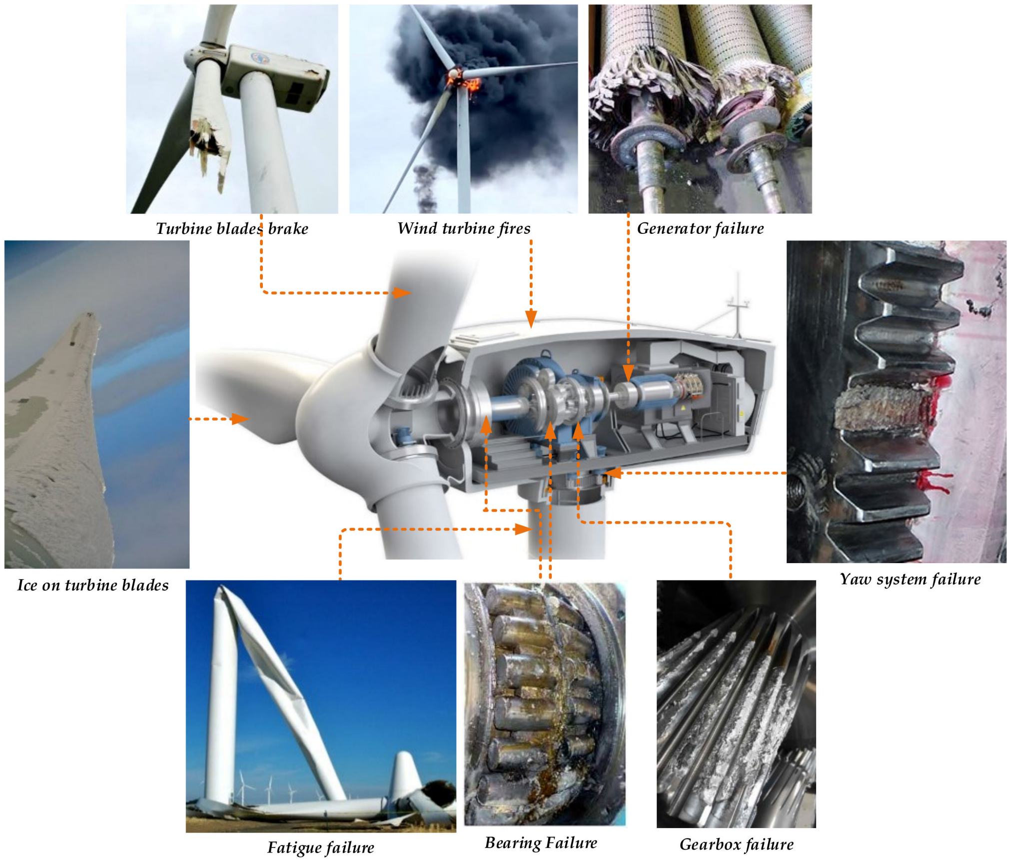


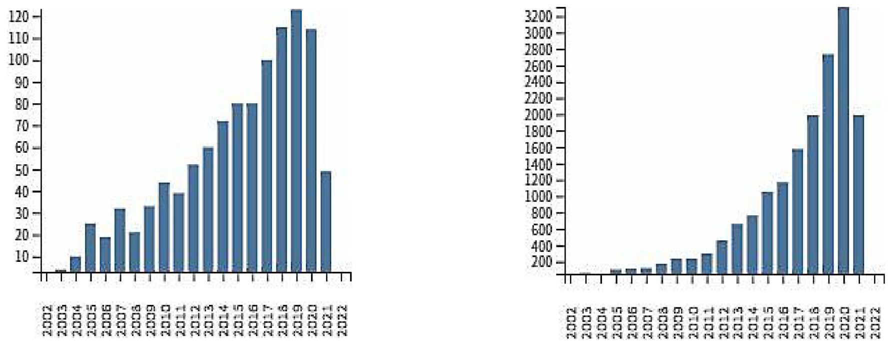
Figure 1. Main components of a horizontal wind turbine, and their corresponding fault.

Since then, PHM technology has revolutionized the amount of product reliability and has led in a wide range of applications, as well as a significant development in several areas, including the fundamental study of failure physics, sensor technologies, feature extraction, fault diagnostics, and classification, and prognostics for failure estimation. These methods have been investigated and used in a variety of sectors. As technologies are deployed and developed in the industry, the number of papers addressing effective applications in many aspects is increasing [5–8].

This clearly shows the rise of this theme and research work in the field is also in a strong trend, as shown in Figures 2 and 3, the PHM citation report for renewable energy, and by incorporating machine learning techniques, respectively. Technical institutions were launched a few years ago to collect and promote experience in many research areas. Since its inception in 2009, the PHM society has organized an annual conference and published the *International Journal of Prognostics and Health Management* (IJPHM) [9]. Since 2011, the IEEE reliability society has sponsored an annual PHM conference (Prognostics) [10]. A minimum of three international conferences is organized each year.

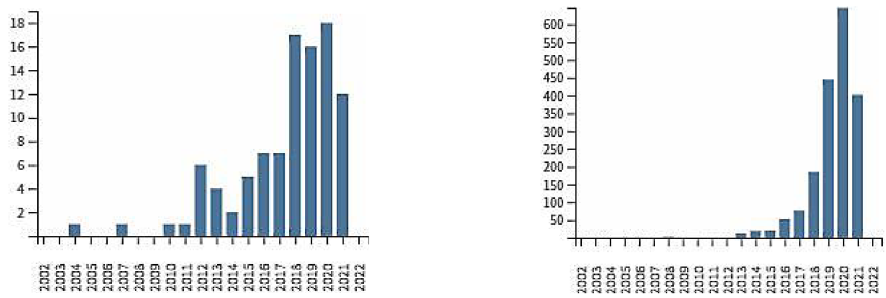
Dedicated to the PHM concept, two of which benefit from the sponsorship of major publishers in the world, including IEEE.

PHM research is now being led by a lot of institutes, some of which are discussed briefly here. The PHM concept is certainly becoming an increasingly visible framework for research work within the scientific and industrial community. Many research laboratories are focused there today; namely, NASA, Prognostics Center of Excellence (PCoE) [11], IMS Center, Army Research Laboratory in the USA, University of Toronto—Canada, CityU-PHM Center University of Hong Kong, FEMTO-ST Institute, Integrated Vehicle Health Management (IVHM) Center, and Green Power Monitoring Systems (GPMS) in the USA, etc.).



(**a**) (**b**)

Figure 2. PHM citation report for renewable energy systems results from the web of science core collection between 2002 and 2021. (**a**) Total publication per year; (**b**) Sum of times cited by year.



(**a**) (**b**)

Figure 3. PHM citation report for renewable energy systems using machine learning results from the web of science core collection between 2002 and 2021. (**a**) Total publication per year; (**b**) Sum of times cited by year.

Recently, there has also been a movement to set standards by professional associations. In the IEEE, PHM standards are discussed by the reliability division and published in related articles [12,13]. In industry, the National Institute of Standards and Technology of the USA has taken similar actions and published a report [14].

PHM has been applied to aerospace and military systems for more than 20 years. PHM could have huge benefits for power generation systems, smart grids, and renewable energy systems such as wind turbine generators, solar panel devices in terms of production, reliability, and maintenance.

Over the last decade, several review papers focusing on the PHM concept from different angles have been published. Sun et al. (2009) investigated some PHM applications in [5], which covered a wide range of applications including defense, aerospace, wind energy, and power electronics. Yin et al. (2016) released a special section in [8] that collects PHM applications in industrial electronics.

Do et al. (2021) proposed integrated PHM control systems for optimal wind turbine and wind farm condition monitoring, to decrease wind energy costs. The focus of the review is on the application of real-time PHM and sophisticated control in wind turbines. The proposed techniques are discussed in terms of their most recent advances, generalization, classification, and comparison.

Various monitoring technologies can be deployed on wind turbines, including vibration analysis, acoustic measurement, lubrication oil monitoring, infrared thermography, and visual inspection. These technologies can be classified into two categories: (i) continuous monitoring techniques and (ii) periodic monitoring.

PHM-based techniques for continuous monitoring of the "health" of wind turbines are widely recognized by the industry as beneficial but economically expensive, especially for onshore turbines. For marine (offshore) and recently installed wind turbines, the deployment of continuous monitoring technology has become almost obvious. The increasing level of deployment of wind turbine continuous monitoring technologies offers an important opportunity for the industry to harness the benefits of PHM to its full potential and reduce operating and maintenance costs. A description of a continuous monitoring system is shown in Figure 4.

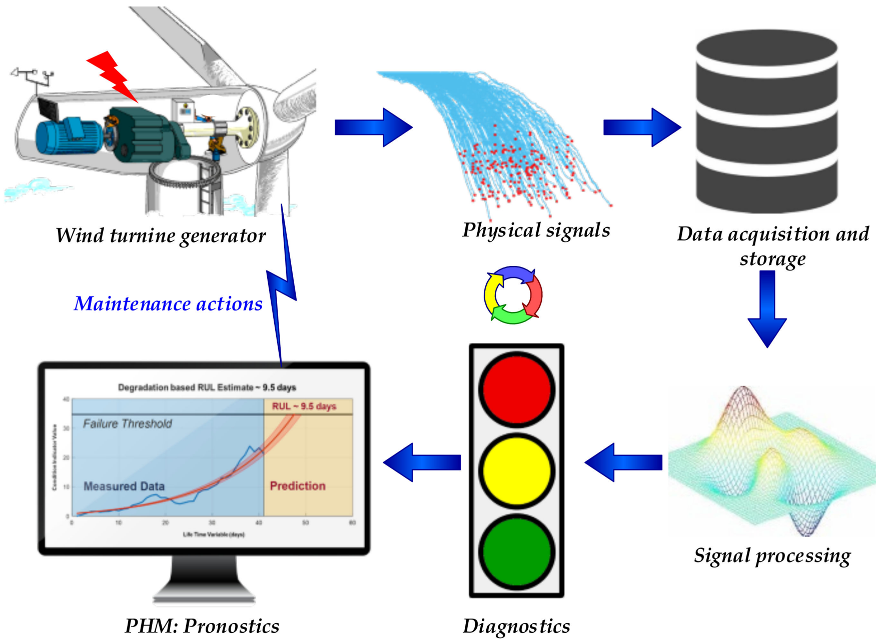


Figure 4. Description of a wind turbine condition monitoring system.

The remainder of the paper is organized as follows: In Section 2, we start by investigating the PHM. In Section 3, PHM approaches are discussed. PHM challenges are given in Section 4. Some PHM applications are presented in Section 5. The final section gives the conclusion.

2. Prognostics and Health Management

2.1. PHM Cycle

Different business procedures are used in industrial monitoring and maintenance to increase availability at a lower cost. Thus, we typically speak about fault detection, failure diagnosis, and the selection of preventative or corrective activities, as well as the scheduling of these actions throughout time.

As shown in Figure 5 [15–17], these steps correspond to; first, to "observe" certain phenomena, then to "analyze" them, and, finally, to "act" accordingly. As previously stated, this being the mind is another strategy that implies attempting to predict the appearance of a phenomenon that has just established itself (failure) rather than understanding it once it has occurred (failure). This is the objective of the prognosis. The PHM cycle is given in Figure 5. The articulation of PHM components can be explained as follows [4,18]:

The purpose of detection is to identify the state of health of the system (in good or defective condition). When a failure is detected, the diagnosis makes it possible to isolate and identify the damaged component; the prognosis then aims to project the state of the system into the future. Then the PHM cycle includes 7 layers [4,15–18]; (1) data acquisition,

(2) data processing, (3) status detection, (4) diagnosis, (5) prognosis, (6) decision, and (7) human-machine interface. More details on this topic can be found in [1–4].

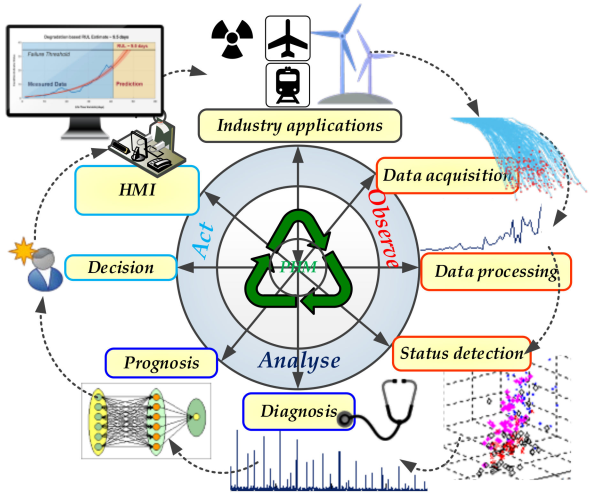


Figure 5. PHM cycle. Reproduced from [15], Elsevier, and from [16], IEEE.

The main goal of prognosis is to provide useful information to make good decisions. As a result, the first set of metrics is the one that allows the monitored system's risks to be quantified. This metric corresponds to prognostic metrics, the most important of which is the residual time until failure, commonly known as the RUL. A confidence measurement should also be associated to indicate the degree of certainty of the RUL [1–4,15,19]. By way of illustration, let us consider Figures 6 and 7, which show respectively the evolution of the degrading health indicator (HI) and its prognosis, and the RUL as a function of time. The RUL can be defined as the time interval between the current time t_p (after detection of degradation; t_D), and the time when the degradation will reach a failure threshold (t_{EoF}): RUL = $t_{EoL} - t_p$, It is also necessary to be able to judge the quality of the prognosis to decide on appropriate actions. Generally speaking, HIs indicate the level of damage at any given time.

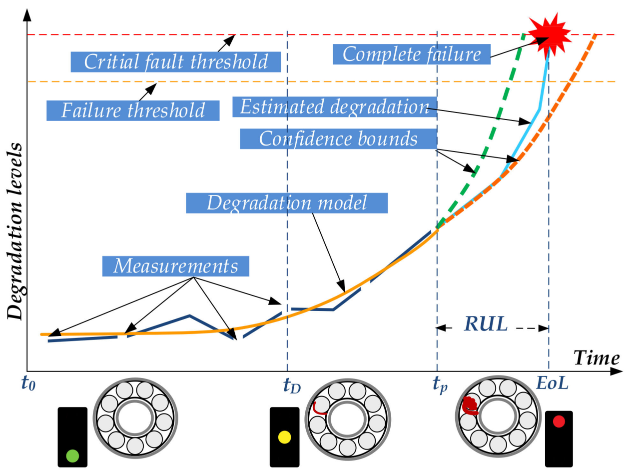


Figure 6. Illustration of the prognostics process.

2.2. Prognostic Metrics

The PHM uncertainties, given in Section 4, can induce dubious prognostic results. The development of methodologies for describing these uncertainties' boundaries and confidence levels for prognosis is a critical step. Building and defining the confidence level of a prognostics system requires a method for assessing prognostic accuracy. As illustrated in Figure 7, the prognosis model is expressed as a probability distribution. Even though there is no common consensus on what metrics should be used to evaluate prognostic efficacy, in open literature some PHM evaluation metrics have been proposed [2,4,19–21]. Prognostics hit rate, false detection alarm rate, missed estimation rate, correct rejection rate, prognostics effectiveness, and other metrics were introduced by Leo et al. (2008) [20] to assess the accuracy of prognostics algorithms. In addition, Saxena et al. (2009) [2] proposed a set of new metrics dedicated for PHM purposes including the prognostic horizon, α-λ performance, relative accuracy, cumulative relative accuracy, and convergence, which were shown in Figure 8. These metrics were applied to a combination of different algorithms and different datasets.

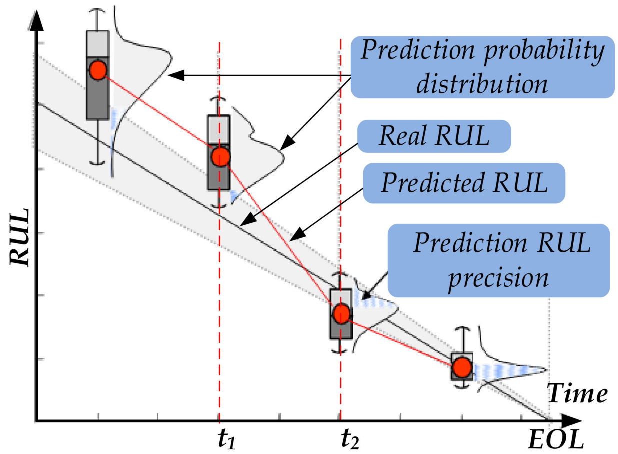


Figure 7. RUL and associated performance metrics.

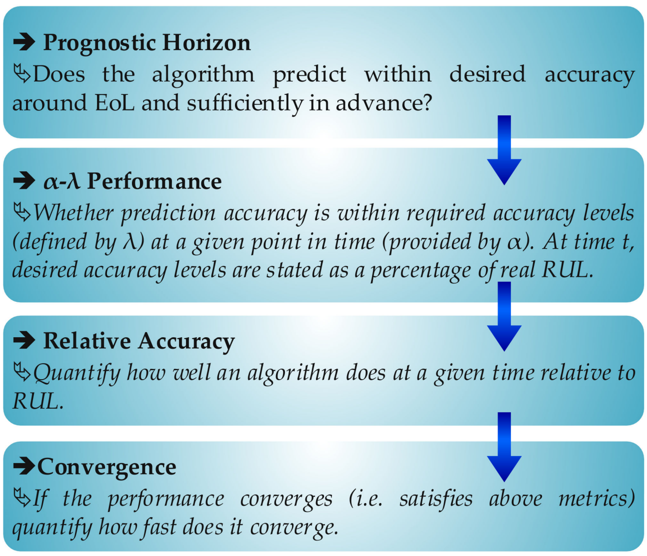


Figure 8. Prognostics metrics. Reproduced from [2], PHM Society and from [4], Springer.

An important step in developing predictive algorithms is to identify HIs, features in the system's data that will behave predictably as the system deteriorates. The HI can be any feature that is useful to distinguish healthy from faulty state or to predict the RUL.

The choice of a method for HI extraction depends mainly on the type of data collected, and the considered application [1–5,18–24]. As highlighted in Figure 9, the HI can be found using signal-based and model-based methods. Degradation models estimate RUL by predicting when the HI will cross a certain threshold. These models are most useful when there is a known value of the used HI that indicates failure. The two commonly available degradation model types are the linear degradation model and the Exponential degradation model.

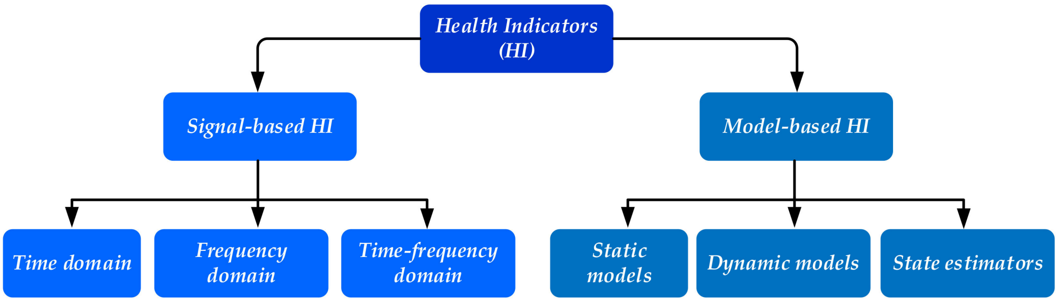


Figure 9. Designing HIs using signal-based and model-based methods. Reproduced from [25].

The linear degradation model describes the degradation behavior as a linear random process with an offset term. When the system does not experience cumulative degradation, the linear degradation model is useful [25].

The exponential degradation model describes the degradation behavior as an exponential stochastic process with offset terms. The exponential degradation model is useful when the test component undergoes cumulative degradation.

Degradation models work with a single HI. However, we can use principal component analysis or other fusion techniques to generate a fused HI that incorporates information from more than one HI [2,4,18,19,26–28].

In this regard, Saxena et al. (2009, 2010) [2,18] proposed a set of metrics for evaluating key elements of RUL predictions, including "prognostic horizon (PH)", "timeliness", "precision" and "accuracy", etc. These metrics are detailed in [1,2,4]. In all cases, these are measures of difference between the estimated RUL and the actual RUL (see Figures 6 and 7).

3. Review of Prognostics Approaches

This section explores the methods of prognostics as part of PHM. Prognostic estimates future damage/degradation and the RUL of systems based on the collected data.

Over the last decade, many methods of prognosis failure have been provided to characterize prognostic approaches [2,4–9]. The instruments used for prognosis are based on the nature of the data obtained and previous knowledge of the system being monitored, while the methods of prognosis are based on the type of intended application.

The PHM process can be classified into two categories: physics-based and data-driven approaches, as well as a hybrid approach, termed hybrid prognosis, as reported in [4]. This classification tends to make consent within the scientific community for the PHM.

3.1. Prognosis Based on Physical Models

Model-based prognostic methods necessitate the development of a physical model that fully describes the degradation process and dynamic behavior of the global system or a subsystem, as well as the integration of degradation phenomena (primarily fatigue and discharge models) whose evolution is modeled by a deterministic statistical physical law or a stochastic process [1,2,4–10,15–19,29,30].

These strategies are more accurate than the other two approaches in most cases (data-driven and hybrid). The models' applications are limited, however, because they are typically constructed under ideal conditions with numerous assumptions. Furthermore, obtaining the best appropriate dynamic model in an analytical form incorporating the phenomenon of real degradation is difficult, if not impossible, at times; yet, numerous simplifying hypotheses are imposed to obtain a model that is close to reality. Furthermore, a model created for a well-defined application may not always translate to another physical system, even if it is of the same type (capitalization by feedback). The application framework of this method is still limited.

3.2. Data-Driven Prognosis

These approaches are based on the exploitation of monitoring data from the various sensors installed around the system to be monitored, which are pre-processed to extract information on the dynamic system behavior as well as its degradation. These data are subsequently used as a database of training dataset for prediction models based mainly on artificial intelligence, present and future states of the system, and thus provide a priori an estimate of the RUL with confidence bounds. Moreover, it is the most used and most developed approach, with research based on the use of neural networks and their variants, support vector machine [1–9,20–24], probabilistic methods (Bayesian networks, Markov models and their derivatives) [1,4,31–36], stochastic models [21,33,35,37–43], state and filtering models (Kalman filter and their variants, particle filter, etc.) [4,15,43–54], regression tools (support vector regression and their variants) [45–49,54], or combinations of different methods [4]. In addition, the Gaussian process (GP) regression [4,17,49–54] is a commonly used method among regression-based data-driven approaches, etc. A comprehensive review of various data-driven algorithms has been carried out by Nam-Ho et al. (2017) in [4].

These approaches do not require an analytical model and their implementation is relatively simple. However, they lose precision depending on the quality of the data collected. They thus represent a certain compromise between applicability and precision.

3.3. Hybrid Prognosis

A hybrid prognosis method is the combination of a physical degradation model and a data-driven approach to improve the prediction capability. Hybrid approaches have good estimation and prediction performance. They allow good modeling of uncertainties. On the other hand, they can be very consumption in algorithmic complexity and are also limited by the need for physical modeling of degradation phenomena.

A review paper by Nam-Ho et al. (2017) [4] contains more information regarding hybrid techniques.

Although not frequently specified in the literature, the prognosis can be assimilated with the combination of two fundamental processes: a prediction process (the RUL estimation) and a clustering process (specifying whether the system belongs to one state or another), these two processes are illustrated by Figure 10. In a nutshell, data-driven prognostic approaches aim to:

- Either to predict the evolution of a situation's HI and then to identify the system's state through classification.
- Either to identify the current state, by classification, and then to estimate its future state.

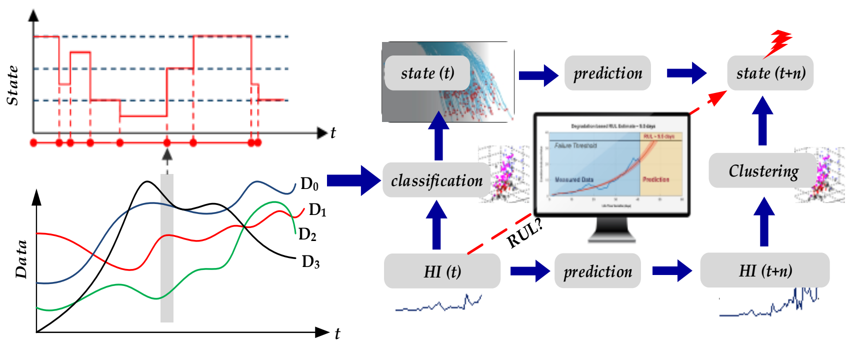


Figure 10. Prognosis processes: prediction and clustering.

The techniques used in these two prediction and clustering methods try to approximate a function that can explain an output vector based on the available measures (input vector). This role is unknown in data-driven prognosis and will need to be identified.

Table 1 summarizes the main advantages and disadvantages of the three prognostics approaches reported in this subsection.

Table 1. Prognostics approaches.

Prognostics Approaches	
Advantages	**Disadvantages**
Data-driven approaches	
- Relatively simple and rapid to deploy. - Aids in the assessment of massive amounts of data to acquire a better knowledge of bodily dynamic system behavior.	- There are no physical cause and effect relationships used. - It is difficult to strike the right balance between generalization and learning specific data trends. - Requires large amounts of data.
Physics-based approaches	
- Based on modeled cause-effect correlations, the prediction results are intuitive. - Only calibration may be required for different cases once a model has been built. - Drives sensing requirements.	- Developing models is not trivial. - High-fidelity models can be computationally costly to run, making them unsuitable for real-time applications.
Hybrid approaches	
- No necessity for high-fidelity models or big data. - Maintains the model's intuitiveness while explaining observed data. - Assists in the handling of uncertainty.	- Requires both data and the models. - A faulty model or noisy data can lead each other's approaches to be biased.

4. Challenges in Prognostics

While the PHM has numerous benefits, it also has several challenges that need to be addressed in future research [2,4–8,53,54]. The classification of prognostic techniques is not a goal in and of itself, and the distinctions across tool types are not often clear. A Bayesian network, for example, can be used to create a dynamic model of a system (model-based approach). It is possible to achieve this by using a series of algorithms to train the network's topology and parameters (data-driven approach). Particle filters are, once again, based on the expression of a hidden state model that is updated based on sensor observations; as a result, they are sometimes referred to as a data-oriented or model-based tool.

Given the constraints imposed by the availability of measurements and/or models, the dynamics of systems, etc. It appears that no prognosis approach is universal and that the choice of an appropriate technique depends on these constraints limiting the applicability of the tools, we can mention for example:

- Modeling uncertainties (numerical errors, unmodeled phenomenon, dynamics, and complexity of real systems): unknown level of uncertainties arising due to lack of knowledge or information.
- Input data uncertainties (initial state (damage) estimate): experiments can be used to characterize the process's inherent statistical variability.
- Measurement uncertainties (sensor noise, loss of information during preprocessing, approximations, and simplifications): unknown number of uncertainties stemming from the collection or processing of data. Feature extraction: to have meaningful prognostics, it is important to collect data that is directly related to damage.
- Operating environment uncertainties (unforeseen future loads, unforeseen future environments, variability in the usage history data).

In terms of technical approaches, physical-based models, data-driven approaches, or the combination of them (hybrid approach) can be used. However, when the physical approach is used, the developing models is not always trivial, and the high-fidelity models may be computationally expensive to run, i.e., impractical for real-time applications.

While data-driven approaches are easier to implement, we have fewer simplifying assumptions, almost used in many applications with relatively low costs. Therefore, it is important to collect meaningful data that are directly related to damage. Although not frequently specified in the literature, the prognosis can be equated with the association of two fundamental processes: a prediction process (estimation of the RUL) and a classification process (specifying whether the system belongs to one state or another), these two processes are explained in detail in [2,4].

The effectiveness of a prognostic tool depends on the accuracy with which the uncertainty immanent to this process is assessed [1,3–5]. Thus, particular interest was focused on the robustness and reliability of the prognosis. Indeed, the confidence that can be allocated to the "prognosis" is an aspect that is still largely open. Moreover, in practical applications, the choice of a suitable technique depends on several constraints thus reducing the applicability of the tools applied, including the availability of measurements, knowledge, system dynamics, implementation constraints (hardware and software architecture), measurement possibilities (sensors, SCADA, etc.), etc. Thus, the prognosis is a task that poses real locks of implementation and validation of the results. These points are the challenge of the research carried out.

There are many different ways to view the challenges of PHM which are outlined in Table 2 [2,4,18]. While there are so many challenges in the PHM (Table 2), there are also many benefits, which are also outlined in Table 2. The main benefit may be the reduction of total life-cycle cost, as is addressed in Table 2.

Table 2. Benefits and challenges for PHM. Reproduced from [15], Elsevier.

Benefits of PHM	
Benefits in life-cycle cost	- Lower operational costs - Increased revenue
Advantages in system design and implementation	- Perfect system design - Improved reliability prediction - Improved logistics support system
Benefits in production	- Better process quality control - Integrated maintenance development by OEMs [1]
Benefits in system operation	- Reinforcing system safety - Enhanced operational reliability
Benefits in logistics support and maintenance	- Condition-based maintenance - Improved fleet-wide decision support - Optimized logistics supply chain - Decreased maintenance-induced fault
Challenges in PHM	
Requirements specifications: - How might a necessity for prognostics be presented in light of uncertainty? - How to identify and attain the prognostic fidelity you want? Uncertainty in prognostics: - To what extent does a prediction's probability distribution reflect reality? Validation and verification: - How can a system be evaluated to see if it meets the requirements? - Is it possible to evaluate the success of prognostics both offline and online?	

[1] Original equipment manufacturer.

5. Prognostics Applications

5.1. PHM of High-Speed Shaft Bearing Wind Turbine (HSSB)

The experimental setup is described in Figure 11. The vibrations were collected by “GPMS” in the USA. For 50 days, vibration data from a 2.2 MW Suzlon wind turbine were recorded at a 100 kHz sampling frequency (i.e., one acquisition every 6 s). Figure 12 shows the vibration trend over 50 and the variation of the kurtosis values as a HI as a function of the number of days, it is obvious that the spectral kurtosis (KS) is a useful indicator for the process of prognosis (monotonous and trendable). The estimation result using the SVR is given in Figure 13. This result shows that we fall on the correct RUL on the 50th day, with a margin of uncertainty.

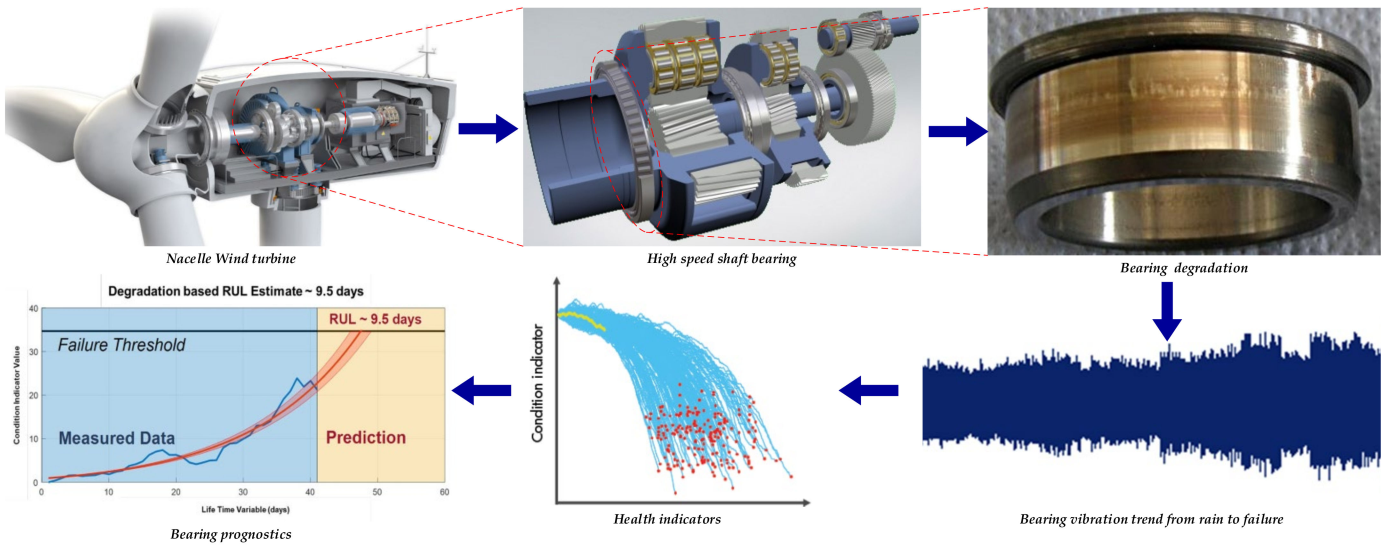


Figure 11. Experimental setup for HSSB wind turbine prognosis.

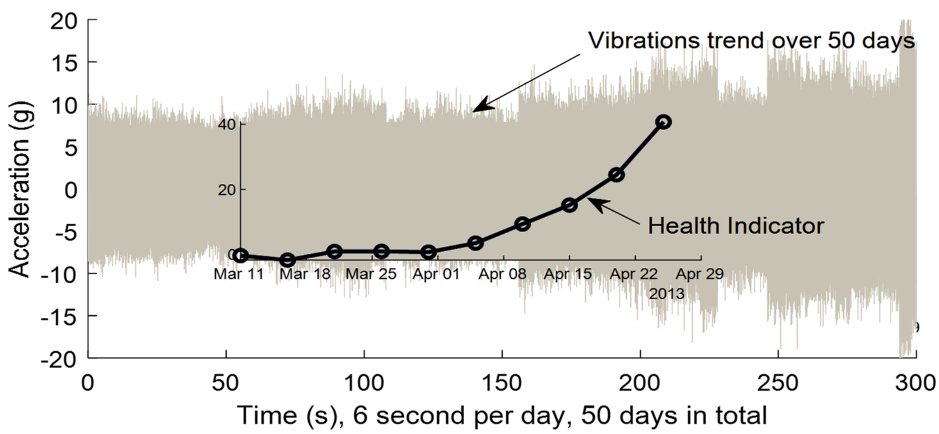


Figure 12. The vibration trend of the HSSB inner race fault: values of the kurtosis for 50 measurements. Reproduced from [49], IEEE.

5.2. PHM of High-Speed Shaft Bearing Wind Turbine (HSSB) Based on Physics-Based Approaches

Physics-based approaches consider that a physical model describing the degradation behavior is accessible with usage conditions such as loading information. In this subsection, we introduce a prognosis method based on the hybrid approach (physical model and collected data) with confidence bounds. As we have seen previously, the severity of the degradation exponentially increases with time, and suddenly this evolution is similar to the prediction model. We give in this PHM application the Paris model (Paris and Erdogan

1963) and the smoothed Kalman filter for the RUL estimation of the HSSB described in the previous subsection, this RUL is predicted with confidence intervals.

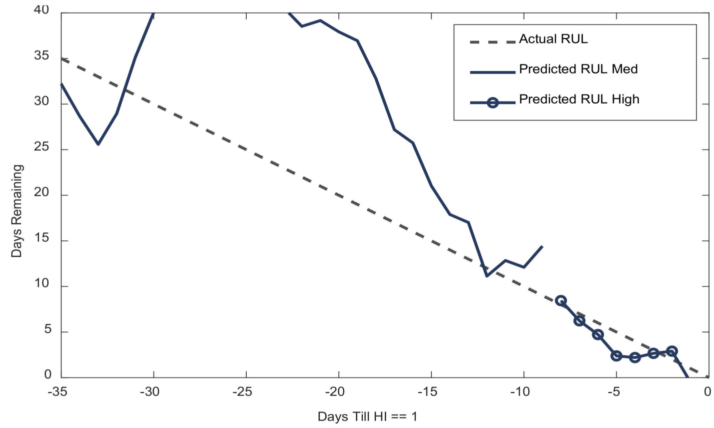


Figure 13. Bearing degradation RUL prediction results. Reproduced from [15], Elsevier.

More details about the application of application the Paris model can be found in our previous paper [15].

The obtained results given in Figure 14 show that the Kalman smoother is an effective way to improve trending and RUL estimation.

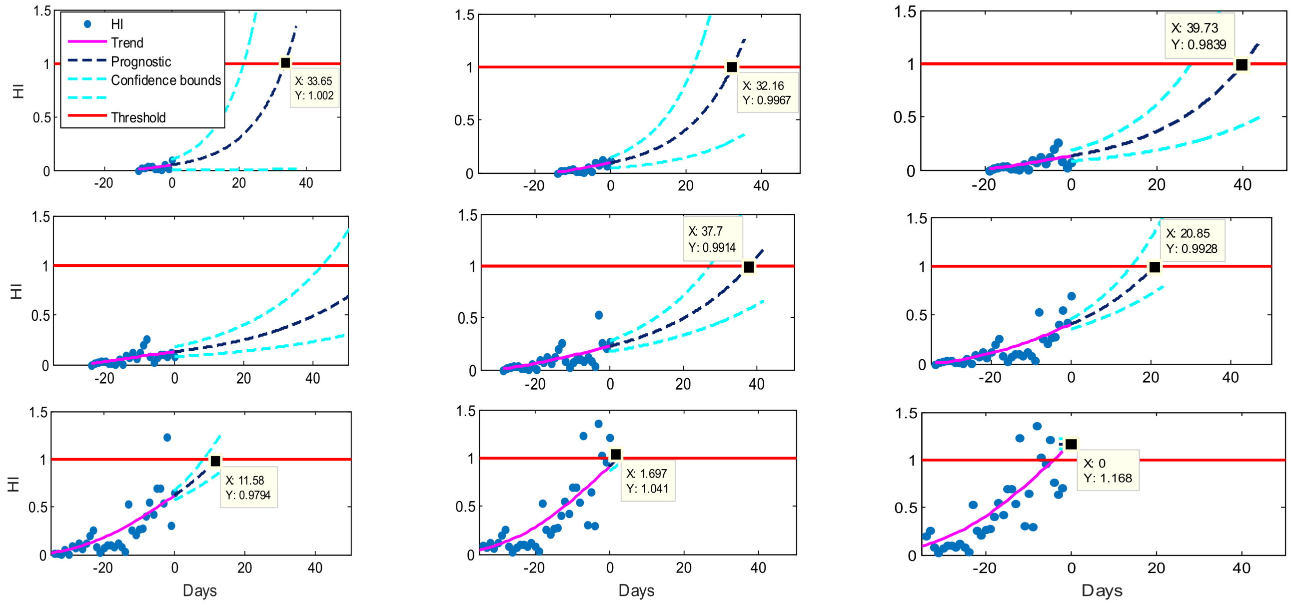


Figure 14. Estimated RUL every five days from initial low to the last high confidence prognostic with error bounds. Reproduced from [15].

5.3. PHM of Wind Turbine Electronic Power Converters

5.3.1. RUL Estimation for Thermally Aged Power IGBT Based on a Modified Maximum Likelihood Estimator

The main objective of this application is to use the combination of the statistical and machine learning approaches to predict abnormal functioning of electronic devices [47]:

Thermally aging the insulated gate bipolar transistor (IGBT) platforms and data are available in [52]. The results of the deterioration level estimation for three IGBT examples with varied measurements are shown in Figure 15. The anticipated RUL across cycles is depicted in Figure 16, where the predicted RUL for the three IGBTs scenarios remains in the accuracy zone throughout all prediction cycles and until the EoL of the IGBT component.

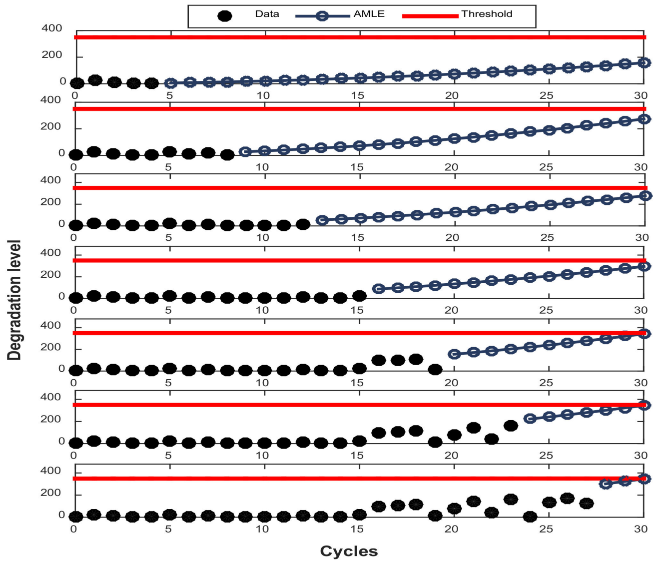


Figure 15. Degradation level with a different number of data points. Reproduced from [51], Wiley.

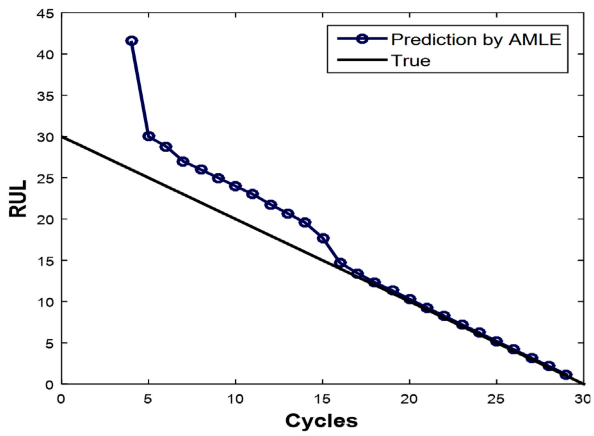


Figure 16. Actual and estimated RUL. Reproduced from [51], Wiley.

5.3.2. RUL Prediction of Thermally Aged Power IGBT Based on Gaussian Process Regression

An effective IGBT failure prognostics approach for predicting the RUL and EoL with high prediction performances was proposed in this application [17]. The proposed failure prognostics method is based on a study of the collector-emitter voltage (V_{ce}) signal's behavior. The time-domain analysis is used in the suggested failure prognostics method, which converts the precursor signal V_{ce} into a HI. It also looks into how to predict the RUL using the Gaussian process regression (GPR) approach.

Figure 17 presents the estimation results of the degradation level for three IGBT cases. Four examples of available measures are considered in this figure. In each scenario, the predicted damage level, based on the three IGBTs available data, is updated. After the last acquired measurement, the prediction stage begins. Failure can be predicted using data-driven methodologies and the proposed prognostic strategy, as shown in Figure 17. The predicted RUL of the three IGBT components' failure is depicted in Figure 18, which is realized using the proposed GPR method. Because it represents remaining life, the convention for RUL plots is that the graph begins with the initial x-axis at 15 cycles and progresses to the remaining cycles, which equals 90 [45,51].

5.4. Power Storage Systems: Predicting Battery Discharge

The lithium-ion battery degradation experiment data used in this application are from the NASA Ames PCoE [1,11]. In this work, Battery #5 from the NASA dataset was used. The capacity degradation experimental results of Battery #5 based on linear regression, polynomial regression are shown in Figure 19 (left) and (right), respectively [51]. Real capacity degradation varies from the linear regression estimates. This reinforces the requirement for a more capable regression model to determine a more precise state of health. Then, as illustrated in Figure 20, the particle swarm optimization-based SVR (PSO-SVR) technique is used to estimate the capacity degradation of Battery #5. To improve prediction accuracy, the PSO method is used to optimize SVR parameters in this study [53].

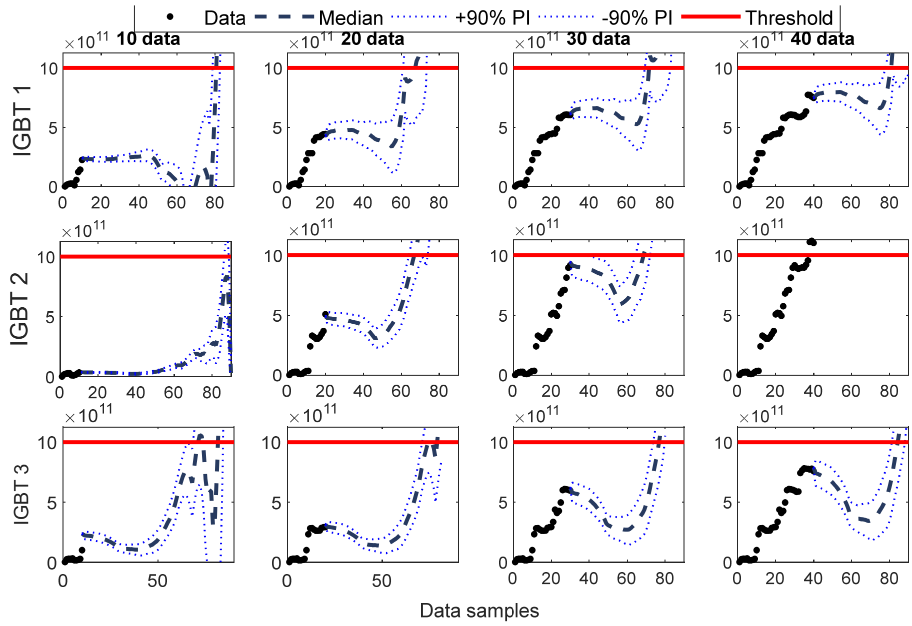


Figure 17. Degradation level under three cases with a different number of the available measurement data point. Reproduced from [17], IEEE.

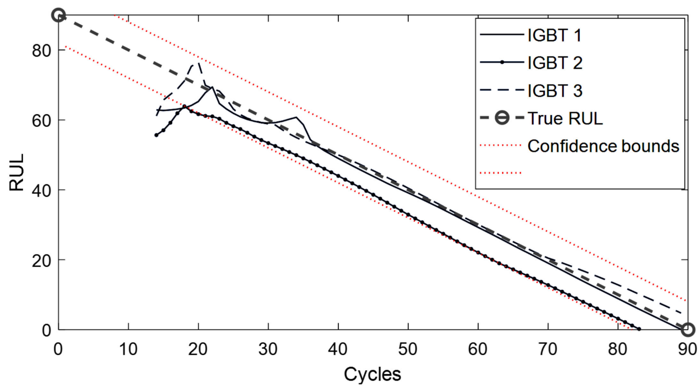


Figure 18. IGBT component predicted RUL. Reproduced from [17], IEEE.

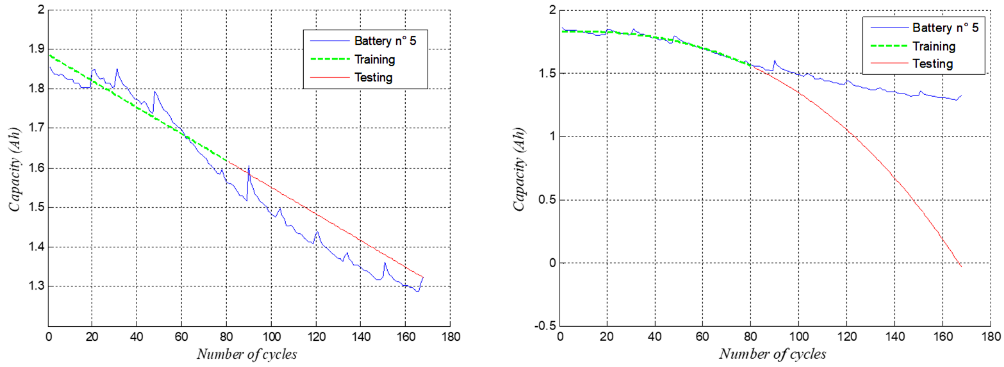


Figure 19. Capacity degradation and RUL prediction of Li-ion Battery #5 (**left**) based on linear regression, and (**right**) polynomial regression. Reproduced from [52], SAGE.

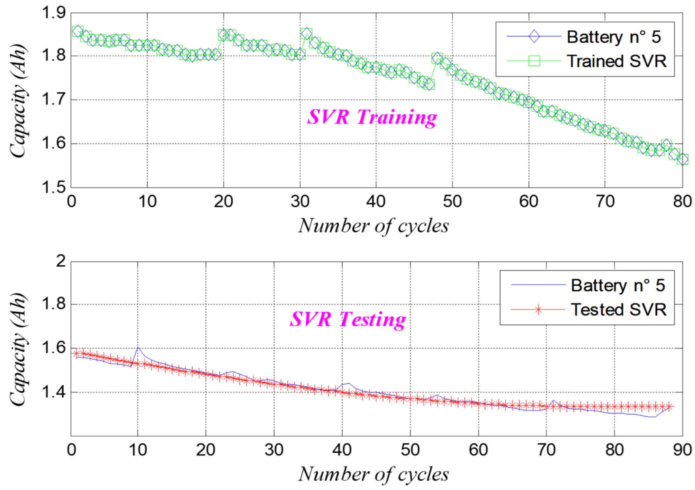


Figure 20. Capacity degradation and RUL prediction of Li-ion Battery #5 based on PSO-SVR ($[C, \varepsilon, \gamma] = [0.3, 2.0359, 19.8 \times 10^{-6}]$). Reproduced from [12], InderScience.

6. Conclusions

In this review paper, the basics of PHM are presented along with historical backgrounds, industrial applications, reviews of recent publications, and benefits and challenges of PHM.

Some applications of prognostics in industry applications are highlighted, including damage in bearing, power converter devices, and batteries capacity degradation.

Based on the review of different results and analysis given in this paper, it can be concluded that the RUL presented thoroughly the PHM applications part are satisfactory compared to the current level of prediction capability in the open literature. However, there are still several challenges to be resolved. First of all, the HI trend decreases exponentially, which can make a large difference in EoL prediction with a small perturbation of threshold. Second, the presented results are principally based on the vibration data. So, since bearings under real operating conditions may last a very long time, massive data should be acquired and stored. Lastly, the presented results are based on the vibration signal. Physical model behavior and explanations of the observed features are not available yet.

Future studies on the current topic are therefore required to deal with uncertainties and their effects on the prognosis results for complex systems.

Author Contributions: Conceptualization, L.S. and M.B.; methodology, L.S. and M.B.; formal analysis, L.S. and M.B.; investigation, L.S. and M.B.; writing—original draft preparation, L.S.; writing—review and editing, L.S. and M.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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