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State-of-the-Art in Integrated Prognostics and Health Management Control for Utility-Scale Wind Turbines

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Abstract

Wind energy takes an important role in the transformation of the global energy system towards clean and sustainable sources. The main development of wind energy technology in recent decades is the growth of wind turbine size motivated by economic factors. The larger turbine size helps to increase power output and energy efficiency, however, it leads to challenges in wind turbine operation and maintenance. To further reduce the cost of wind energy, advanced control approaches are developed focusing on power maximization, structural load mitigation, lifetime extension, and reliability improvement. This multi-objective problem is difficult to solve due to design conflicts. The optimal trade-off between goals is varying and depends on actual operating situations such as on-site wind characteristics, system aging, and grid requirements.

Modern utility-scale wind turbines are equipped with numerous sensors providing useful information about turbine components operation status. With the huge development of computation capability and big data analytics techniques, the turbine performance and state-of-health information could be obtained and evaluated through historical logged data using Prognostics and Health Management (PHM) systems. The information aids the optimal operation and maintenance of wind energy systems.

In recent years, the integration of state-of-health information into the closed-loop control system begins to attract the attention of the wind energy researcher community. Controllers are adapted based on current and future aging behaviors optimizing the trade-off between service life expansion and power production maximization. This paper provides a review of integrated prognostics and health management control systems for optimal operation and maintenance of wind

turbines and wind farms reducing the cost of wind energy. The review focuses on the combination of on-line PHM and advanced control for wind turbines. State-of-the-art, future trends, and open challenges of the approach are provided and discussed.
Keywords: wind energy, integrated PHM control, prognostics and health management, fault evasion, structural load, O&M cost

1. Introduction

Global warming is a major consequence of high carbon dioxide emissions due to the burning of fossil fuels. In 2018, coal-fired power plants account for 37 % of the European Union Emissions Trading System (EU ETS) emissions [1]. In addition, the use of fossil fuels also emits mercury, sulfur dioxide, nitrogen oxides, and particulate matter into the air and water leading to many health problems [2]. These factors in combination with the depletion of fossil fuel motivate the requirement for low-carbon and renewable energy sources.

Wind energy plays a significant role in scaling up renewable electricity sources for the decarbonization of the energy industry. It is forecasted that more than 30 % of electrical demand by 2050 is provided by wind power [3]. To fulfill the growing requirements, wind turbines are scaled up in size to access more power from the wind driven by technology innovation and the use of advanced materials. The largest wind turbine was installed in 2018 with a power rating of 8.8 MW and a rotor diameter of 164 m [4]. Larger rotors aid in increasing capacity factor and efficient ultimately reducing the cost of wind energy. The wind levelized cost of energy (LCOE) has been reducing in the last decade [5, 6]. In the US, the average rotor diameter in 2018 increased by 35 % over 2010, while the average LCOE reduced by over 50 % in the same period [7]. The production cost of wind energy is still higher than that of conventional technologies using fossil fuel, however, it is expected to be lower by 2020 [8].

The larger turbine size improves power output and energy efficiency, however, it leads to challenges in wind turbine operation and maintenance. Larger and more flexible turbines experience

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higher mechanical stress on the turbine components. These structural loads may lead to early failure limiting the turbine size and performances [9]. To further increase the turbine size, structural loads need to be reduced or considered/monitored.

Advanced control approaches are applied for utility-scale WTs to maximize power production and reduce structural loads [10]. The variation of turbine components such as blades, tower, drive-train, or gear-box are controlled along with the power production by modifying the blade pitch angles. When the structural loads are considered, it is helpful to understand the wind turbine as a multi-input multi-output (MIMO) system. Because of the coupling between control inputs and outputs, traditional single-input single-output (SISO) controllers are difficult to design and not suitable for such systems [11]. Multi-input multi-output control approaches consider system internal connections so they can realize multiple objectives simultaneously. Multi-objective advanced MIMO control algorithms reduce the loads while maximizing the power generation. Related control approaches need to be robust and able to reduce the effects of unknown variable wind speed disturbances and modeling errors [12]. Load mitigation helps to expand the turbine lifetime, reduce the maintenance cost, and allows to build larger WTs. However, load reduction often comes with the consequence of decreasing power production and increasing blade pitch activities [9]. Balancing and optimizing this trade-off is challenging and still is an open problem.

To make wind energy more competitive, the related cost of energy (COE) needs to be reduced either by evolution in wind turbine (WT) design, applied materials or optimal operation and maintenance (O&M). The O&M cost can account for 30 % of wind power COE [13, 14], so it is important to reduce the cost by expanding the turbine service lifetime or reducing unplanned maintenance cost which takes over 50 % of total O&M cost [15].

To diminish the unplanned costs due to failures, Prognostics and Health Management approaches are recently developed for wind turbines to provide the information of turbine state-of-health (SoH) and prediction of the remaining useful life (RUL) [16]. Using the measured data, maintenance schedules of each component of the turbine and each turbine of the wind farm can be optimized to minimize the overall maintenance cost while guaranteeing the failure probability thresholds [17]. The maintenance strategy using health condition monitoring is classified as condition-based maintenance (CBM). Diagnostic and prognostic information about the system's health allows making suitable decisions on emergency actions and repairs. Condition-based or predictive maintenance (CBM) techniques are adopted to reduce the wind turbine probability of failure thus to reduce the O&M cost [17]. The main challenge of wind turbine CBM is the uncertain wind makes it is difficult to predict future health degradation behavior [18]. The complexity in the signal analysis technique for WT PHM also hinders the real-time application of the approach [19].

Unscheduled maintenance due to failures can be reduced using fault-tolerant control (FTC) systems to improve the system reliability and survivability [20]. The FTC systems are designed to continue the turbine operation at reasonable performance in case of restrictive faults [21]. The effects of faults are accommodated by modifying or switching the related controllers with sacrifices in power production [22]. Real-time monitoring of systems is needed for detection and isolation of faults. Applying FTC allows avoiding the entire turbine failure resulting in total losses of power generation. However, due to the fact that the turbine operates with faulty components, the power output is restricted. Repairs are required to make the system operate with full capacity.

The FTC approach works only when a fault is detected, or the system is already in a faulty condition. To avoid the fault, control strategies need to be adapted with system health indicators before the fault appears. The idea of integrating knowledge about system SoH and predicted RUL into the control loop to adapt the controller targeting system safety and reliability was first introduced in [23]. The concept named Safety and Reliability Control Engineering (SRCE) considers the reliability function and lifetime extension of the system by continuously optimizing control strategy based on the information provided by PHM systems (fig. 1). With this concept, system reconfiguration decisions are made not only at the faulty conditions but also when changes in the system reliability are detected. The approach allows optimizing the system dynamic behavior and reliability characteristics in the fault-free state.

In [24], online information from an PHM system is used to adapt the control law to current and future fault and contingency situations with the so-called Prognostics-enhanced Automated Contingency Management (ACM+P) approach. The system life can be managed by considering future assumptions in control law if performance requirements can be relaxed. The ACM+P system can accommodate faults or mitigate failures using short-term prognosis (with a RUL estimate

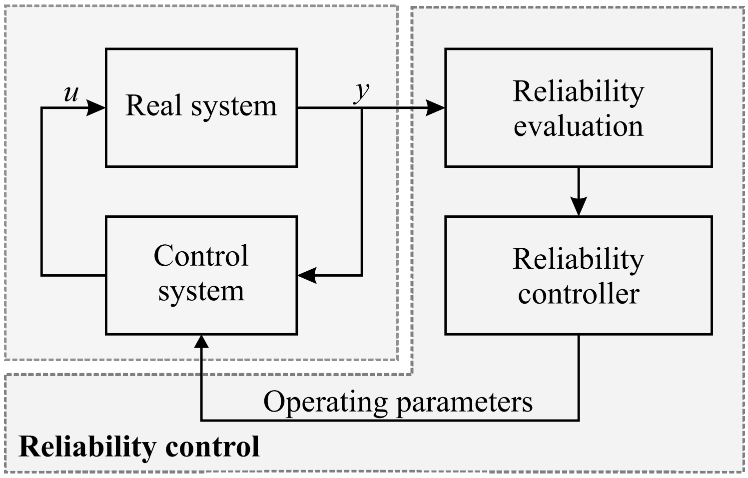

Figure 1: Safety and Reliability Control Engineering (SRCE) concept

in terms of minutes or hours in the future) by reconfiguring controllers or/and control objectives accordingly. Similar idea to consider and control the current and future system SoH is proposed in [25, 26] with the related paradigm name Health-Aware Control (HAC). The HAC concept allows adapting controllers before faulty events happen improving the system reliability and providing wider space to optimize the maintenance schedules. The decision-making concerns control objectives, maintenance, and repairs strategies can be integrated into a closed-loop automation concept considering system SoH, safety, reliability, and performance. The system components aging is also monitored allowing situation-based optimal operation of the system depending on the actual degradation level.

Recently, there are several reviews on PHM approaches and advanced control for wind turbines [10, 27, 28, 22]. The review [10] focuses on load mitigation multi-objective control schemes for large-scale wind turbines. The trade-off between power maximization and structural load reduction is pointed out in the paper as an open problem. The authors of [22] provided references about model-based fault detection and fault-tolerant control approaches for WTs to improve reliability. Signal-based methods for WT fault detection are reviewed in [28]. The paper gives a detailed description of sensor types and measurement techniques for WT structural health monitoring. An evaluation of the online applicability of the methods is also provided in the review. Commercial aspects of PHM methods are considered in [27]. The authors review data-mining techniques for

WT structural health monitoring used commercially. The cost, advantages, and disadvantages of each approach are also discussed.

The aforementioned reviews only focus on PHM or control, the integration of PHM into the control loop is only briefly discussed. Applying integrated PHM control (IPHMC) approaches allows the improvement of system reliability and performance ultimately reducing the O&M cost. The approaches require reliable and online SoH monitoring methods. The knowledge about the health degradation characteristics and the relation between system dynamics behavior and health degradation are important to establish optimal control strategies. Most of the research focuses on condition-based maintenance and fault-tolerant control applications [29, 30]. Recently, the combination of PHM and control applied for non-faulty wind turbines to avoid unwanted failure begins to attract attention. There are several names for this strategy such as contingency control [31] or health aware control [32], however, the overall idea is the integration of PHM information into control systems to improve performance and reliability of fault-free systems. With the development of digitalization and data-driven techniques, the integration approaches have the potentials to further improve the wind energy system performances. Till now, there was no throughout review on this new research direction for wind energy systems. So it is necessary to generalize and provide the most recent developments in the field for establishing research gaps and challenges.

This paper focuses on the combination of PHM and advanced control approaches with the application for wind turbines and wind farms to improve the reliability and cost-effectiveness of wind energy. Requirements of PHM and control approaches for the combination are reviewed and discussed. Unlike previous reviews focusing on fault-tolerant control, this contribution considers also fault-evasion control, which is the adaptation of the control system for non-faulty conditions to avoid faults. The paper aims to provide the state-of-the-art in integrated PHM control for large-scale wind energy systems. The generalization and classification of the approach are given for the first time. Challenges and requirements for the further development of the concept are also discussed.

The contribution is organized as follows: Section 2 introduces the general concept of IPHMC. Wind turbine health diagnostic and prognostic techniques focusing on control integration ability is provided in section 3. Section 4 reviews and classifies existing IPHMC approaches applied for wind turbines. Finally, conclusions, open challenges, and future trends are given in section 5.

2. Integrated PHM Control Concept

The general concept of Integrated PHM Control (IPHMC) applied for wind energy systems (WESs) is described in fig.2. The WESs could be wind turbines or wind farms with related controllers. The WEC control systems realize contradictory multiple objectives such as power production maximization, power reference tracking, structural load reduction for lifetime extension, or/and improving system reliability. The priority of each objective varies depending on specific situations. For example, when the wind turbines/farms operate in a tough condition, such as strong wind turbulence intensity, it is more important to reduce structural load than to maximize the instantaneous power harvested. The objective is to operate the turbine at reduced power without exceeding some damage thresholds resulting in unscheduled downtime [31]. The trade-off needs to be optimized by control reconfiguration for each particular situation defined by the prognostic and diagnostic modules. In any case, system health-related information such as aging condition, accumulated damage, failure probability, and predicted RUL are important aspects and need to be considered.

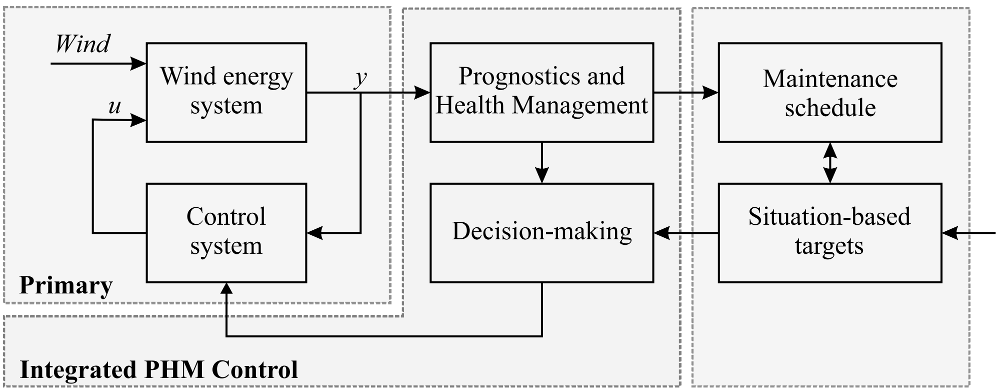

Figure 2: IPHMC concept for wind energy systems

Unlike traditional FTC approaches, the IPHMC framework allows adapting the control action even when the system is still in a non-faulty situation or before the fault appears [25]. The idea is to not only control the physical states of the turbine (speed, power, bending moment, etc.) but also the health-related characteristics (fatigue damage, RUL, reliability, etc.) as indirect values obtained from the PHM modules [23]. The PHM module acts as a virtual sensor providing real-time feedback for the SoH control loop. Decisions are made using the heath status information and other requirements depending on each specific operating situation. The output of the decision-making module is the reconfiguring of controllers and/or reference values to accommodate the change of SoH, changing of control objectives depending on situations, or even stop the whole system. The maintenance schedule of system components also could be considered to adapt the control law minimizing the overall cost.

3. Prognostics and Health Management for Wind Turbine Control

The goal of the PHM module is to calculate the health status and estimate the remaining useful life of wind turbine components. The obtained information is used for optimal operation, maintenance, and control of wind energy systems. In the field of wind energy, fatigue damage is widely used to assess health status wind turbines and is recommended by the IEC 61400-1 standard [33]. Fatigue is the weakening of a material due to cyclically applied loads which are beyond certain thresholds [34]. Accumulated fatigue damage can express the aging of the system thus providing helpful information for optimizing the health degradation behavior. Because the fatigue damage generally can not be measured directly, methods to calculate the accumulated fatigue damage are needed. Fatigue calculation methods suitable for wind turbine control are introduced in the next section.

3.1. Fatigue damage calculation

An overview of methods using for calculating wind turbine fatigue damage is provided in [35]. The fatigue calculation methods can be classified as counting methods, spectral methods, stochastic methods, and hysteresis operators. For complex loading caused by varying wind speed, the rain flow counting (RFC) algorithm [36] in combination with Miner's rule [37] has the most accuracy. However, the method has some drawbacks that make it difficult to combine this with control applications. Hence this contribution focus on RFC and solutions for control applicability of the method.

3.1.1. Rain flow counting

For certain materials, the relation between the number of cycles to failure with the stress level or cycle amplitude was established. This relation can be represented by the stress-cycle (S-N) curve. The S-N curves are typically derived from experiments on samples of the material. For a given stress history, assuming there are k different load amplitude levels, namely $S_i, (1 \leq i \leq k)$, each level S_i appear in n_i cycles, and the number of cycles to failure at the stress level S_i is N_i defined by the S-N curve. The damage accumulation D_{ac} can be calculated using Miner's rule as

$$D_{ac} = \sum_{i=1}^{k} D_i = \sum_{i=1}^{k} \frac{n_i(S_i)}{N_i(S_i)}, \tag{1}$$

with D_i denotes contributed damage of stress level S_i and D_{ac} denotes accumulated damage over the whole time history. In general, when the damage accumulation D_{ac} reaches a defined limit ≥ 1, the system is considered as failed.

To define stress levels and the number of cycles of each level, the rain flow counting (RFC) algorithm is used. The algorithm transforms a spectrum of varying stress levels to a set of simple stress range allowing the application of Miner's rule (fig. 3).

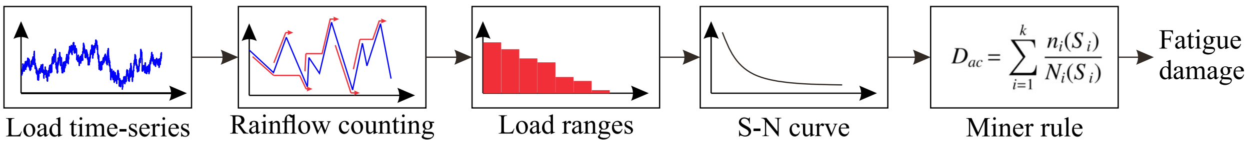

Figure 3: Fatigue damage calculation using RFC and Miner rule

The RFC algorithm is widely used to calculate the fatigue damage with the most accurate regarding complex loading [35]. However, the standard form of RFC is computationally expensive due to the requirement of the whole load history. The RFC method is an procedure rather than a mathematical function [35, 38]. The relation between fatigue damage and the measured stress obtained from the RFC algorithm is typically nonlinear and difficult to compute the gradient.

To reduce the computational and memory load, the RFC method can be realized on a floating time window rather than the whole time history [39, 38]. An online RFC algorithm is proposed in [40]. Instead of tracking the complete time history data, the algorithm store and processes extremal value (minimum and maximum) simultaneously as they occur to provide the equivalent full and half cycles.

3.1.2. RFC approximation

As mentioned in [35], RFC algorithm is widely used and has an active standard [41]. However, the approach is nonlinear and not differentiable make it is difficult to apply the approach directly for control. Typically for control integration, the RFC algorithm is approximated using mathematical models.

In [32], the RFC algorithm is approximated using a linear model establishing the relation between the generator torque T_g, system states ω_r, disturbance v_w with the damage z of the blade

$$\begin{aligned} z(k) &= \frac{m}{L}(a_0 + a_1\frac{\partial P_g}{\partial \omega_r}\omega_r(k) + a_1\frac{\partial P_g}{\partial T_g}T_g(k) + a_2 v_w(k)) \\ Z_{acc}(k+1) &= Z_{acc}(k) + z(k), \end{aligned} \tag{2}$$

here Z_{acc} denotes the accumulated damage, P_g the generator power output, L the number of samples per cycle, and m the slope of the accumulated damage curve. The model parameters a_0, a_1, and a_2 is obtained using least square algorithm using the results from RFC. Figure (4) shows the comparison between the fatigue damage calculated from RFC and the approximated model.

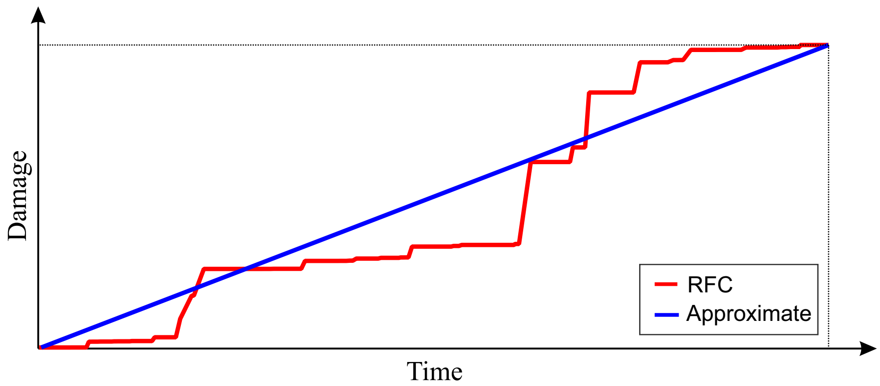

Figure 4: Linear approximation of RFC algorithm

A recursive ARX model is used in [39] to approximate the relationship between the tower damage equivalent load (DEL) and the tower top velocity. Damage equivalent load, which is a constant-amplitude fatigue-load defining the equivalent damage as the variable spectrum of loads

[42], can be calculated using the results of the RFC algorithm. The approximated model is used as a damage sensor for a sliding mode controller to reduce the fatigue damage of the turbine tower.

In [38], a nonlinear autoregressive networks with exogenous inputs (NARX) artificial neural network (ANN) is for the function approximation. The tower fatigue damage is calculated from the stress time series using RFC for different wind speeds. The obtained stress and damage data is used for training and testing of the ANN. Several ANNs with a different number of neurons are considered. The results show that ANNs can approximate the RFC algorithm with high accuracy. The number of neurons required is low thus integration of the model does not increase much the computational time.

3.2. Remaining useful life estimation

Remaining useful life (RUL) is a mandatory information for optimal operation and maintenance of wind energy systems. Based on the RUL information, suitable maintenance and control strategies can be chosen to reduce the O&M cost and improve system reliability. Remaining useful life estimation methods are broad and can be classified considering different aspects. Roughly, wind turbine RUL estimation methods are grouped as model-based, data-based and hybrid approaches [43, 44].

Model-based methods aim to establish physical or mathematical degradation models to represent the correlation between input signals and RUL. The models are built based on the knowledge about the mechanisms leading to failure such as wear, fatigue damage, crack growth [45]. Wind turbines contain multiple failure modes driven by different mechanisms thus it is difficult to establish a model covering all of the modes. Typically, only dominated phenomena are considered. For wind turbine applications, the most common model-based method is the fatigue life prediction based on the S-N curve and Palmgren-Miner rule [43]. The accumulated fatigue damage D_k of a component at the time T_k can be calculated from historical measured data using (1). When the accumulated damage reaches a predefined limit D_f, the component is considered as failed. Assuming that the wind turbine operates in the same conditions in the future, the time to failure L_f is estimated as

$$L_f = \frac{T_k}{D_k} D_f. \tag{3}$$

The estimated RUL is calculated as

$$RUL = L_f - T_k = T_k(\frac{D_f}{D_k} - 1). \tag{4}$$

Data-based or data-driven approaches depend on measured data, detailed knowledge about system physics is not required. The methods establish the correlation between RUL and physical signals by learning from stored data. Multiple failure modes can be presented without knowledge about the failure mechanisms behind, however, great efforts need to be put into obtained and process failure data. The quantity and quality of data greatly affect the prediction accuracy [45]. Typically, raw data from measurement systems need to be processed using noise reduction and feature extraction techniques before using for training the data-driven models.

Artificial neural networks (ANN) are used to model the normal behavior of wind turbine gearboxes in [46]. Possible anomalies or faults can be detected according to the difference between the real measured output and estimated output from the models. The time remaining still the failure or remaining useful life is predicted using another ANN model. The prediction ANN model represents the dynamics of the difference between real and estimated data (residual) of a historical failure case. The residual dynamics of the system can be predicted using the ANN residual model and current gearbox life status. The remaining useful life can be predicted if the failure can be detected by the ANN normal behavior model.

In [47], a regression model and ANN are combined to model the relationship between wind turbine bearing variations and health status. The regression model provides the bearing degradation information through the root mean square of vibration signals. The results from the regression model are used to improve the ANN RUL prediction. The combined model shows better accuracy than the single ANN model.

Stochastic data-driven models based on probability and statistical theory such as Bayesian networks, Markov process, or Levy processes are also used for fault detection and RUL estimation of wind turbines [43]. The methods consider deterioration behavior as random processes and provide RUL prediction results as probabilities [48]. Stochastic methods can deal with uncertainties in measurements and parameters, however, they require the observation of health or degradation indicators. Based on the data, the most fit stochastic model need to be chosen for good predictions [43]. The authors of [49] use an interval whitenization Gaussian process (IWGP) to estimate RUL of wind turbine bearings. The effects of the non-stationary operation of wind turbines on health indicators are reduced using the interval whitenization methods. The RUL prediction model is established using the processed health indicators and Gaussian process.

A model-based and data-based hybrid approach for WT RUL prediction is proposed in [44]. The method applies a physical-based approach to model the normal and faulty operation behavior of the system. The obtained models are used for generating related normal and faulty data. A data-based clustering algorithm is used to separated the simulated data into clusters representing normal operation and different failure scenarios states. An on-line monitoring system continuously measures data from the real system to identify and calculate the Euclidean distance between the current operation cluster and identified clusters from the previous off-line step (fig. 5). When the degradation process begins, the current cluster of the real system will move toward a faulty cluster. The distance and the degradation speed to the faulty cluster are used to calculate the related RUL.

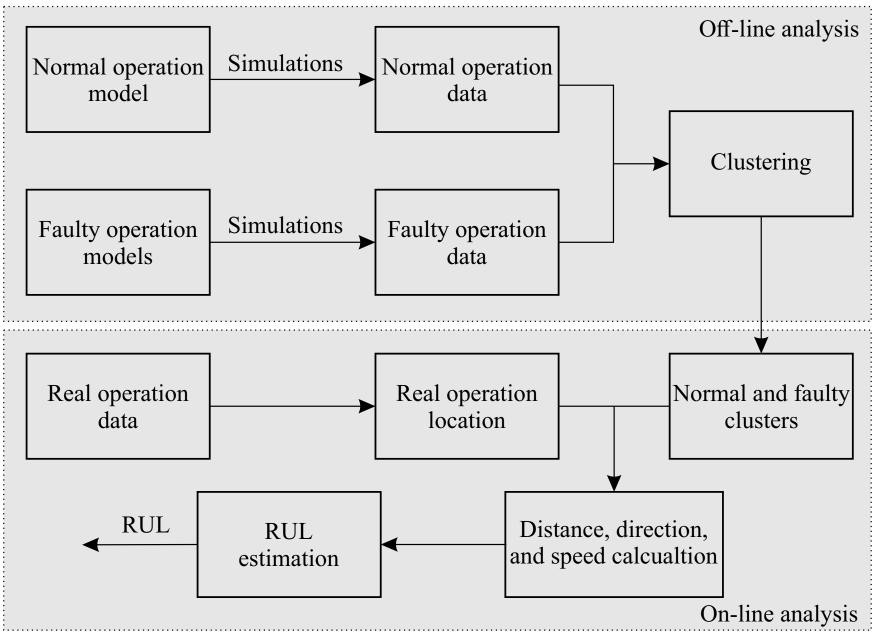

Figure 5: Hybrid RUL prognostic (redrawn from [44])

Wind turbines are complex systems operating in non-stationary conditions due to varying wind speeds. Wind turbine components also are affected by various fault mechanisms. These make it is difficult to estimate accurately the RUL of WT components. Generally, several approaches are combined to deal with WT prognostics and diagnostics challenges such as non-stationary operating conditions, the lack of labeled data, or multi states degradation. These combinations often require complex computation thus limit on-line applications [19, 18]. For integrated PHM control, the problem becomes more severe due to the requirement of quick reactions against the change in health status and health degradation behaviors. So the development of accurate and simple enough diagnostic and prognostic methods is crucial for the applicability of the IPHM strategy.

4. Integrated PHM Control for Wind Turbines

System health diagnostic and prognostic techniques are widely applied to wind turbine operation and control to improve system reliability reducing O&M cost. The existing IMPHC approaches for wind turbines can be briefly classified into two categories: direct damage control [50, 32, 39, 38] and reliability adaptive/supervisory control [31, 51, 52, 53].

4.1. Direct damage control

Structural load reduction is one of the main objectives of large wind turbine control. Most of the current load mitigation control methods reduce the load indirectly through the reduction of certain norms of measured signals such as stress variations [50, 38]. The control performance is evaluated later through measured outputs using some off-line metrics like root mean square (RMS), power spectral density (PSD), or damage equivalent load (DEL) [54]. Direct damage control strategies use on-line PHM modules as virtual sensors providing damage information thus allow to control the damage directly [39] results in more effective and flexible load mitigation control schemes.

Model predictive control (MPC) is used in combination with an on-line estimation of the turbine shaft fatigue damage in [50]. Fatigue damage is considered as the weakening of materials subjecting to cyclic stress so it can represent the system's health status. In the wind energy control field, fatigue is often reduced indirectly by variation suppression of wind turbine components.

Within the IPHMC context, fatigue damage is integrated directly into the control loop as a feedback measurement. The on-line fatigue estimation is based on using a Preisach hysteresis operator. The operator provides similar results as the rain-flow counting (RFC) method, however, the proposed method does not require a large history measurement data so it is more suitable for on-line applications. The estimated damage information is used to modify the weighting matrix Q adding extra weights to the cost function of the original MPC algorithm. The accumulated damage is reduced without deterioration in output power using the extra health information.

In [32], a health-aware MPC algorithm for wind turbines is proposed. A linear approximation version of the RFC model for on-line application is used to provide the blade fatigue. The damage linear equation is included in the MPC algorithm state-space model as a new output, an additional objective corresponding to damage is added to the MPC cost function. Depending on the feedback health value and the corresponding weight of the damage reduction objective, the health-aware MPC de-rates the wind turbine producing less power and accumulated damage. A trade-off between maximizing the extracted power and minimizing the accumulated damage is observed and needs to be optimized.

Nonlinear model predictive control (NMPC) is used in [38] considering tower fatigue load reduction and energy maximization. The fatigue damage is estimated via an artificial neural network (ANN). The cycle-based fatigue damage obtained from the RFC algorithm is transformed into a time series by calculating the damage for each segment of time. Parameters of the ANN is trained using the obtained damage time series. Eventually, the estimated fatigue damage using ANN is included directly in the cost function of the NMPC controller. The proposed strategy considers the fatigue in closed-loop control thus can directly minimize the fatigue damage.

A virtual fatigue sensor for on-line damage estimation is presented in [39]. Fatigue sensing is based on the application of the RFC algorithm to a floating window defined in the time domain instead of the whole stress time series. The use of time windows reduces the computational burden of the classic RFC and provide the damage as a function of time. For control integration, the damage function is approximated in the least-squares sense using a recursive ARX model. A sliding mode collective pitch controller with fatigue damage feedback is used in combination with a standard generator torque controller to mitigate the turbine tower damage. The approach is able to reduce the tower damage equivalent load (DEL) with the exchange of power output reduction.

4.2. Reliability supervisory control

Reliability adaptive/supervisory control schemes focus on improvement/control of WT reliability using current and future health status provided by PHM modules. Generally, the approaches have a cascade structure with a primary control loop realizing structural load and power regulation objectives (fig. 2). An adaptive/supervisory control loop reconfigures or modifies the set-point of the primary control loop according to the feed-back health status information for reliability control. Fault-tolerant control is one case of reliability supervisory control for faulty systems. The primary controller is reconfigured depends on faults detected by health diagnostic algorithms (fig. 6). The goal of FTC is to ensure the system's reliability avoiding serious failures that may stop the system.

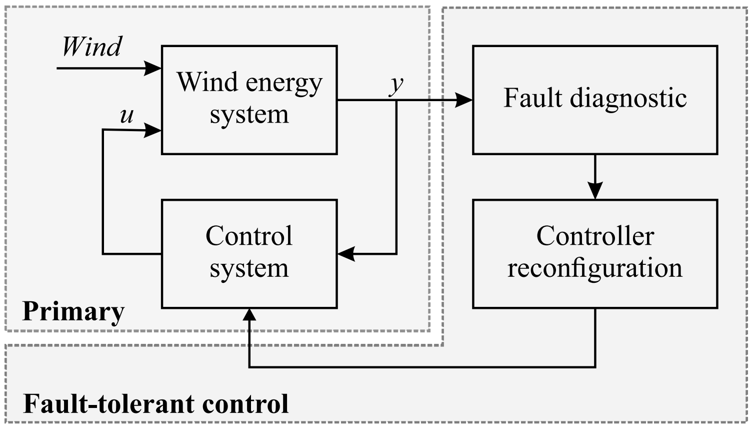

Figure 6: Fault-tolerant control

Reliability supervisory control approaches also can apply for non-faulty systems. In this case, the control system reconfiguration is realized before the faults appear. The approaches depend on the observation of health indicators representing system health status and RUL prognostic information.

In [31], a structural health management system is integrated with contingency control to deal with the trade-off between power production and the potential blade damage. The goal is to operate the turbine at a reasonable reduced capacity avoiding extreme damage caused by the blade

SoH deterioration and highly turbulent operating conditions. The heath indicator used is the blade stiffness obtained from recorded blade tip deflections through proper models. Base on the provided health information, the contingency controller may de-rate the turbine with a proper value to prevent exceeding some damage threshold resulting in unscheduled downtime. The information about operating conditions defined by measured wind characteristics is also considered in the paper. In the case of highly turbulent wind, the turbine power set-point is smoothly reduced by the contingency controller to ensure system safety and reliability.

A method to control the remaining lifetime of the WT component is proposed in [51]. Here the term 'remaining lifetime' denotes the average time until the component fails in the current operating conditions. The remaining lifetime is adjusted so that the WT components can survive to the next maintenance schedule avoiding unwanted repairs. A PHM module is required to determine the health status and estimate the remaining lifetime. The health status indicates the likelihood of failure of the component and is classified by levels using several thresholds. Depending on the health status level and remaining lifetime, the suitable control scheme regarding different power degradation level is selected to maximize the profit. In the contribution, the health status is obtained from simple measured temperature, vibrations, and stress data, no signal analysis method is given. The remaining lifetime is determined through a function of time that WT spends on each power level, the parameters of RUL function are obtained from the experiment data via regression methods. The authors suggested that the control scheme can be selected automatically or manually based on additional operational requirements. However, there is no guideline for establishing control schemes.

In [52, 53], the optimal trade-off between generation power and lifetime extension is considered. The structural load reduction or lifetime extension level is determined by the observed fatigue damage accumulation. An on-line RFC algorithm is adopted to provide the fatigue damage as the system health indicator. The on-line RFC algorithm considers the extreme values of the measured time series as they occur instead of processes the whole spectrum reducing the computational time and providing instantaneous damage value. Depending on the health status of the turbine components defined by the accumulated fatigue damage, the optimal distribution between power production and structural load mitigation is made. Different MIMO controllers are precomputed with respect to different load mitigation levels defined by different weights. Higher structural load mitigation capacity leads accordingly to lower power production. The controllers are designed by the LQG technique, different levels of load mitigation are realized by tuning the corresponding elements of the LQG weighting matrices. The decision of sacrificing harvested power to improve lifetime is made with support from the structural health monitoring systems. The ultimate goals are to improve system reliability and minimize the overall cost.

The switching between different controllers is triggered by damage accumulation thresholds in [52]. The aging of the turbine is considered by the damage diagnostic and prognostic model. At first, the power production is maximized without considering load reduction. When the accumulated damage reaches a certain predefined threshold due to system aging and/or failures, the load mitigation controller is activated. The load mitigation level is continuously adjusted depending on the damage level to guarantee the pre-defined turbine service lifetime.

In [53], an additional case of controller selection based on the damage increments or the rate of change in accumulated damage at particular moment information is provided. In this case, when the damage accumulation rate is high due to either strong variation wind or system failures, the load mitigation needs to be high to accommodate the related effects. Otherwise, the controller can ignore load mitigation to maximize power production in the normal working condition. The Remaining Useful Life (RUL) is controlled by switching between different load mitigation levels indirectly regulating the damage accumulation rate. Lifetime control is realized as a secondary control loop affecting the primary load reduction level.

In figure 7 the IPHMC concept is summarized. The direct damage/health control approaches consider the accumulated damage or health status of the system as controllable states. The approaches require the real-time and precise calculation of health indicator features which typically can not be measured directly. The dynamics of health degradation or damage accumulation process also need to be suitably modeled for designing controllers. Most of the existing literature in the wind energy field uses fatigue damage as a health indicator. Fatigue damage and fatigue damage dynamics are typically estimated by approximated models of RFC schemes. However, wind energy systems are complex and contain multiple failure modes driven by different mechanisms thus the obtained models might not cover all of the heath degradation characteristics. Data-driven

PHM approaches can represent multiple failure modes and degradation stages. However, the actual lack of wind turbine run-to-failure data makes it is difficult to train and validate the models. The complexity and computation time of data-driven approaches are also important aspects that need to be considered for real-time control applications.

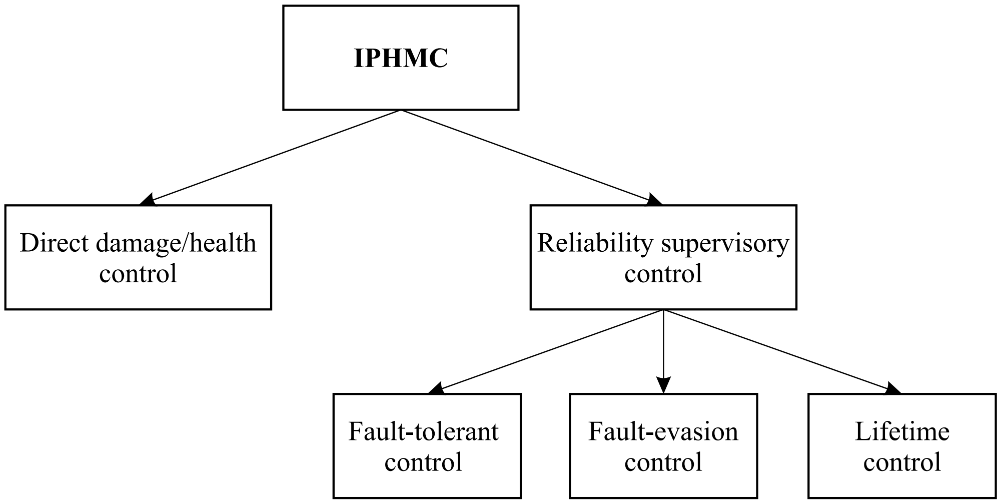

Figure 7: IPHMC classification

The real-time requirements of PHM approaches are relaxed in the reliability supervisory control scheme. Due to the much slower dynamics of reliability characteristics compared to that of wind turbines, the time interval of the supervisory control loop is typically chosen higher than that of the primary control loop. Considerations on the relation between control system configurations and reliability characteristics are required in this situation. Faults can be avoided by reconfiguring the primary controller based on the current and future health status information provided by PHM modules.

Lifetime control is possible using the reliability supervisory control scheme as mentioned in [51]. The remaining useful life of each component can be regulated to reach the next maintain schedules avoiding unscheduled repairs. However, no method is provided yet in [51]. In [52, 53] the RUL is controlled indirectly using damage accumulation thresholds. The required lifetime might not be guaranteed due to the lack of RUL feedback.

5. Conclusions

In this contribution, recently developed integrated PHM control strategies for wind turbines are reviewed. The general concept of IPHMC applied for wind energy systems is provided. An overview of wind turbine PHM approaches is given with a special focus on fatigue damage calculation and RUL estimation. The requirements for control integration of the approaches also are discussed with the solutions using approximation techniques. Integrated PHM control approaches for wind turbines are revised and categorized. The approaches have the potential to improve and control system reliability avoiding faults thus reduce the wind turbine O&M cost. Lifetime control is possible using the approaches by RUL feed-back.

The main challenge of IPHMC approaches is the requirement of reliable and simple enough on-line PHM methods. The methods need to handle various loading operating conditions and multiple failure modes driven by different mechanisms.

The relations between control system configurations and health degradation dynamics are needed for establishing the supervisory control loop. Due to various loading conditions and multiple degradation states, situation-based multiple models may be needed to fully represent the relations.

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