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Reliability Improvement of Wind Turbine Power Generation using Model-based Fault Detection and Fault Tolerant Control: a review

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Abstract

Reliability improvement of wind turbine power generation is the key issue that can turn the wind power into one of the main power sources to respond to the world power demands. The likelihood of fault occurrence on wind turbine components is unavoidable, especially for large rotor modern wind turbines, operating in harsh offshore environments. Accordingly, the maintenance need increases due to unanticipated faults, which in turn, leads to higher energy cost and less reliable power generation. In this regard, model-based fault detection and fault tolerant control techniques have been extensively investigated in the last decade, for achieving good performance. In this way, the reliability, availability and safety features of the wind turbine power generation are also enhanced. Thus, in this paper a comprehensive review of the most-recent model-based fault detection and fault tolerant control schemes for wind turbine power generation is presented, focusing on the advantages, capabilities and limitations. Note that the so-called data-driven or signal-based methodologies, which rely on the analysis of the signals directly generated from the monitored system, are not reviewed in this paper. This review is organized in a tutorial manner, to be a suitable reference for further research for the wind turbine's reliability improvement.

Keywords: Wind Turbines; Model-based approaches; Reliability and robustness; Fault Detection and Isolation (FDI); Fault estimation; Fault Tolerant Control (FTC).

1. Introduction

Ever increasing energy demand is one of the key factors forming the energy research trends. The decrease in exploitable sources, huge environmental pollution, and high price, are some of the most reported problems of the traditional energy resources. As the result of seeking for new resources, the renewable energy resources have been ascertained as an appropriate alternative to traditional fossil fuel energy generation, among which wind energy has demonstrated outstanding characteristics and has attracted the world's attention; therefore, it has been defined as "the world's fastest-growing renewable energy source" with 30% growth annually on average throughout the last two decades [1]. During this time, the planned capacity of wind farms has increased significantly to provide a higher share of the energy. The global wind power installations are illustrated in Figure 1, which also depicts the growth of captured wind power. The wind power extraction of some countries has also been summarized in Table 1, which shows the anticipated growth and demand for wind power. Accordingly, modern wind turbines are designed with a longer blade, to increase the swept area, with higher towers and also to be located in remote offshore places to encounter higher wind speeds, and consequently, to increase the captured power e.g. from 75-kW to 20-MW [2], as illustrated in Table 2.

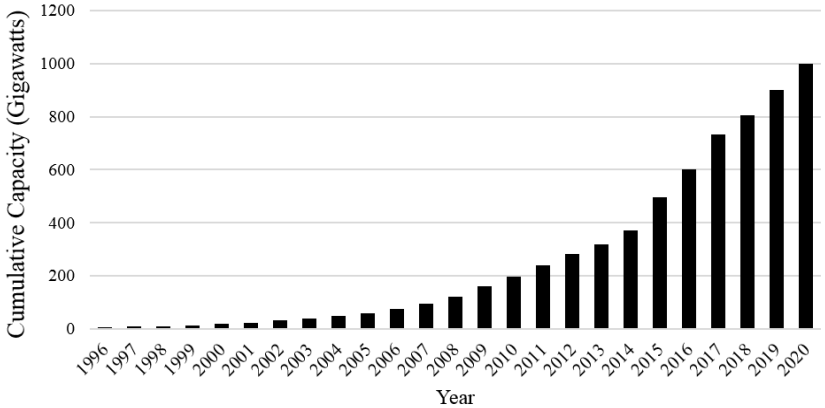

Fig. 1. Global capacity of wind power plant [1, 3].

Table 1. Wind power share of whole power demand for some countries.

Country	Wind power share of whole demand	Expected year	Reference
United States	30% (300 GW)	2030	[2]
European Union	12-14%	2020	[4, 5]
	25%	2030	
China	15%	2020	[1, 4]
Portugal, Spain, France, Germany, Ireland, Sweden	9% to 21%	2015	[1, 5]
Denmark	50%	2020	[6]

Table 2. Wind turbine size increase throughout the last three decades [1].

Blade length (m)	Tower height (m)	Nominal power (kW)	Usage year	Location
8.5	30	75	1980-1990	Onshore
15	45	300	1990-1995	Onshore
25	60	750	1995-2000	Onshore
35	70	1500	2000-2005	Onshore
40	95	1800	2005-2010	Onshore
50	100	3000	2010-present	Onshore
62.5	130	5000	2010-present	Offshore
75	160	10000	Future	Onshore
125	220	20000	Future	Offshore

The operation of large offshore wind turbines in harsh environments and in the presence of highly varying stochastic loads, often leads to the occurrence of faults, requiring increased planned maintenance schedules [7, 8]. This presents the major problem of the lower reliability of wind power generation [9]. Increased maintenance has double negative effects, i.e. higher maintenance cost and also, less generated power due to increased downtime [10, 11]. Accordingly, the cost of the generated energy is generally increased and, consequently, the wind turbine generated power may be less competitive compared to other traditional resources. For example, the maintenance cost of an offshore wind turbine is estimated to be 20-25% of the total income [12-14] and 10-15% for an onshore farm for 20 years of operating life [15]. In Figure 2, the wind turbine failure rates and corresponding downtime are illustrated [8]. It is thus beneficial to keep the maintenance cost as low as possible, decrease downtime and, consequently increase the captured power, and finally improve reliability, despite the presence of faults [16]. For this aim, Fault Detection and Isolation (FDI) and Fault Tolerant Control (FTC) are powerful methods. The fault information captured from FDI units can be used to optimize the maintenance procedures via remote diagnosis [17]. The use of FTC allows the equipment to achieve the required robustness with respect to the considered faults and, consequently, keeps the wind turbine performance at the desired level, despite the presence of faults. So, the maintenance need and downtime are decreased, and the reliability of power generation will be improved. Therefore, the final cost is kept as cheap as possible [18, 19].

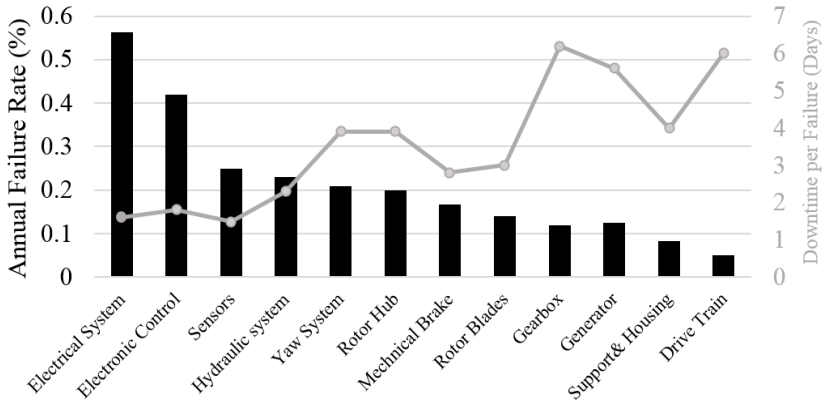

Fig. 2. Wind turbine component failure rate (black color) and downtime (grey color) [8].

The FDI and FTC designs for wind turbines have been significantly developed over the last decade. Most of the works in this field have been motivated by the competitions conducted by KK-electronic a/c and MathWorks from 2009 to 2015 [17]. Accordingly, the number of studies and consequent publications has been increased considerably. In Figure 3, SCOPUS results have been presented to highlight the rapid growth by considering the published journal papers in

the field of wind turbine FDI and FTC, which implies that it currently represents the subject of intensive worldwide research [20]. However, there are only a few available review papers in this field [21-24]. So, it is beneficial to have a well-organized comprehensive overview on the status of recent developments of FDI and FTC techniques for wind turbine power control, to make a framework for future studies, as the motivation of the current paper. Accordingly, in Section 2, the wind turbine model including faults is described. Also, modern wind turbine model representations for FDI purposes are recalled. In Section 3, the different available FDI methods are outlined. Consequently, the FDI methods for each component of the wind turbine are summarized in Section 4. FTC design techniques for wind turbines are sketched in Section 5. Finally, the concluding discussion, future trends on this area and conclusions are given in Sections 6 and 7, respectively.

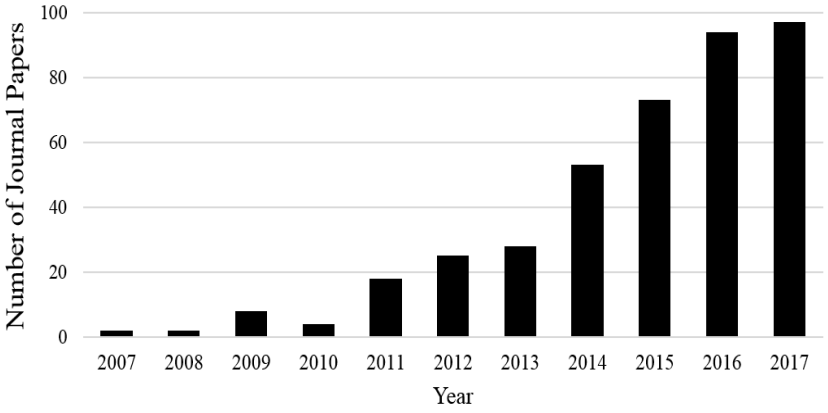

Fig. 3. SCOPUS indexed published journal papers in the field of FDI and FTC wind turbine design.

2. Wind turbine model representation for fault detection purposes

The wind turbine modeling framework specifies appropriate FDI methods. Obviously, the nonlinear model provides the best framework, on which basis it can be used to design the FDI scheme, as it is able to accurately represent the wind turbine behavior [25]. Nevertheless, it leads to more complicated FDI structures. On the other hand, model-based FDI methods have been mostly developed for linear models. Consequently, the linearized wind turbine model has dominated the recent research scope [1, 26-29]. Nevertheless, inconsistency between behaviors of the linearized model and the highly nonlinear wind turbine is significant. So, to have more accurate model representation as well as to take advantage of already-developed FDI methods, two modern wind turbine modelling frameworks have been recently proposed, including linear parameter varying (LPV) and fuzzy Takagi-Sugeno (T-S) prototypes, which are briefly recalled in this section. It should be noted that several high-fidelity wind turbines model packages already exist, e.g. the Fatigue, Aerodynamics, Structures, and Turbulence (FAST) tool developed by NREL [21], and the 4.8MW wind turbine benchmark model developed by KK-electronic A/C and Aalborg University [17]. However, to review the fault sources and effects, the wind turbine model is briefly introduced.

2.1. Nonlinear model and possible faults

The wind turbine operation can be seen as an interaction between wind speed and blades. Accordingly, due to the given aerodynamic profile of the blades, aerodynamic torque and thrust are applied to the rotor shaft, i.e. connected directly to the blades, and nacelle, respectively. The wind speed is usually modelled as the sum of a steady state mean value, and stochastic perturbation terms, considering turbulence and gusts. The mean wind speed is estimated by passing a set of measured wind data through a low-pass filter. On the other hand, the stochastic term can be modelled using Von Karman or Kaimal turbulence models [30]. In addition, the wind shear effect, i.e. variation of wind speed depending on height, and periodic tower shadow effect, i.e. wind speed reduction for the blade passing in front of the tower, are two deterministic terms, for which there are accurate mathematical expressions that can be implemented in the wind speed model [26].

In variable pitch wind turbine types, the aerodynamic performance of the blades can be changed by adjusting the blade pitch angles. The rotor shaft speed is increased and transferred into the generator shaft using a drivetrain in between. Finally, the electrical power is produced in the generator. In variable speed wind turbine types, the electrical generator torque load can be tuned to control shaft speed. All the mentioned components are located in the nacelle at the top of the tower. The applied aerodynamic thrust leads to a fore-aft oscillation of the tower, which varies the effective wind speed at the blade plane. Also, a yaw mechanism is used to rotate and keep the wind turbine perpendicular to the wind direction, measured with a wind vane, although, at the control system level, due to limited yaw rate, i.e. less than 1°/s, the yaw mechanism is often ignored [22].

The blade aerodynamic characteristics can be characterized with $C_p(\beta,\lambda)$, $C_q(\beta,\lambda)$ and $C_t(\beta,\lambda)$, which are power coefficient, aerodynamic coefficient and thrust coefficient, respectively. These coefficients are functions of β, i.e. blade pitch angle and λ, i.e. tip speed ratio, defined as $\lambda = R\omega_r/V_r$, where R is blade length, ω_r is blade rotor angular speed and V_r is the effective wind speed at the rotor plane. These coefficients are often available as numerical lookup tables or empirical equations for a given blade profile. The aerodynamic torque T_a, power P_a and thrust F_t, are as,

$$T_a = \frac{1}{2}\rho A R V_r^2 C_q(\beta,\lambda),\ P_a = \frac{1}{2}\rho A V_r^3 C_p(\beta,\lambda),\ F_t = \frac{1}{2}\rho A V_r^2 C_t(\beta,\lambda), \quad (1)$$

respectively, where, ρ is air density and A is blade swept area as, $A = \pi R^2$. Also, the power coefficient can be represented as $C_p(\beta,\lambda) = \lambda C_q(\beta,\lambda)$. Considering fore-aft oscillation of the nacelle, due to F_t, the effective wind speed can be represented as a relative velocity as, $V_r = V_w - V_n$, where V_w is the free wind speed before encountering the blades and V_n is the projected nacelle velocity in the wind direction. Considering modern wind turbines with three independent pitch actuator mechanisms, the resultant aerodynamic torque can be written as,

$$T_a = \frac{1}{6}\sum_{i=1}^{3}\rho A R V_r^2 C_q(\beta_i,\lambda), \quad (2)$$

where, β_i is the pitch angle of the i^{th} blade.

Long term operation of the wind turbine may lead to debris build-up on the blades, due to dirt or ice, and erosion. This changes the blades aerodynamic characteristics, as deviation of C_p, C_q and C_t mappings from normal ones [29]. The debris build-up effect is modelled as,

$$\tilde{C}_p = C_p + \Delta C_p,\ \tilde{C}_q = C_q + \Delta C_q,\ \tilde{C}_t = C_t + \Delta C_t. \quad (3)$$

In this paper, $\tilde{\chi}$ and $\Delta\chi$ are the new abnormal value and deviation from the normal parameter χ, respectively.

The rotor speed ω_r is increased and transferred into the generator shaft, rotating at ω_g, via the drivetrain, which can be modelled as a two degree of freedom rotational system. Inertia of rotor and generator shafts are J_r and J_g, respectively. Also, the drivetrain speed ratio is N_g and includes torsion stiffness K_{dt} and torsion damping, B_{dt}. This elastic gear meshing results in a torsional angle of twist of the main shaft θ_Δ, which is defined as $\theta_\Delta = \theta_r - \theta_g/N_g$, where, θ_r and θ_g are rotation angle of rotor and generator shafts, respectively. Also, viscous frictions for rotor and generator shaft bearings are considered whose coefficients are B_r and B_g, respectively. The drivetrain efficiency in transferring speed is η_{dt} [26, 31]. The drivetrain model is then written as,

$$\begin{aligned}
\dot{\omega}_r(t) &= -\left(\frac{B_r+B_{dt}}{J_r}\right)\omega_r(t) + \frac{B_{dt}}{J_r N_g}\omega_g(t) - \frac{K_{dt}}{J_r}\theta_\Delta(t) + \frac{1}{J_r}T_a(t),\\
\dot{\omega}_g(t) &= \frac{\eta_{dt}B_{dt}}{N_g J_g}\omega_r(t) - \left(\frac{B_g}{J_g} + \frac{\eta_{dt}B_{dt}}{J_g N_g^2}\right)\omega_g(t) + \frac{\eta_{dt}K_{dt}}{N_g J_g}\theta_\Delta(t) - \frac{1}{J_g}T_g(t),\\
\dot{\theta}_\Delta(t) &= \omega_r(t) - \frac{1}{N_g}\omega_g(t).
\end{aligned} \quad (4)$$

where, T_g is generator shaft torque. The wear or tear of drivetrain gears can be considered to be possible faults in this mechanism, which changes the drivetrain stiffness and damping, considered as, $\tilde{K}_{dt} = K_{dt} + \Delta K_{dt}$ and $\tilde{B}_{dt} = B_{dt} + \Delta B_{dt}$ [17, 18]. This fault happens very slowly with time, but it leads to total drivetrain breakdown which results in long and costly downtime [17].

The pitch actuator is modeled as an underdamped hydraulic mechanism, which is more reliable with little backlash and larger stiffness than the electrical pitch actuator motor. The hydraulic pitch actuator is thus described as a second order dynamic system as,

$$\ddot{\beta} = -\omega_n^2\beta - 2\omega_n\xi\dot{\beta} + \omega_n^2\beta_{ref}, \quad (5)$$

where, ω_n and ξ are the natural frequency and damping ratio of the pitch actuator, respectively. Also, β_{ref} is the reference pitch angle, commanded by the pitch controller and to be followed by blade pitch angle. The operational ranges of the pitch actuator are considered as $\dot{\beta}_{min} \le \dot{\beta} \le \dot{\beta}_{max}, \beta_{min} \le \beta \le \beta_{max}$. In this paper, χ_{max} and χ_{min} stand for maximum and minimum allowable values of the variable χ, respectively. The pitch actuator may suffer from dynamic change which leads to slower response and, consequently, poor pitch angle regulation [32]. Three of the most reported dynamic changes are hydraulic pump wear, pressure drop due to hydraulic leakage and more compressible oil due to high air content in the hydraulic oil. These dynamic changes deviate the natural frequency and damping ratio from normal values [24]. It should be noted that hydraulic leakage is considered as an abrupt fault while oil air content increases slowly. The numerical values of a given pitch actuator dynamic changes presented for a wind turbine benchmark model, [33], are summarized in Table 3, in which PW, HL and HAC stand for pump wear, hydraulic leakage and high air content situations, respectively. $\omega_{n,X}$ and ξ_X are natural frequency and damping ratio, respectively, in the situation X. α_{f_1} and α_{f_2} are fault indicators.

Table 3. Numerical values of a given pitch actuator dynamic changes [33].

	Natural Frequency(rad/s)	Damping Ratio	Fault Indicator
Normal	$\omega_{n,N} = 11.11$	$\xi_N = 0.6$	$\alpha_{f_1} = \alpha_{f_2} = 0$
Pump Wear	$\omega_{n,PW} = 7.27$	$\xi_{PW} = 0.75$	$\alpha_{f_1} = 0.6316, \alpha_{f_2} = 0.29688$
Hydraulic Leak	$\omega_{n,HL} = 3.42$	$\xi_{HL} = 0.9$	$\alpha_{f_1} = 1, \alpha_{f_2} = 0.87853$
High Air Content	$\omega_{n,HAC} = 5.73$	$\xi_{HAC} = 0.45$	$\alpha_{f_1} = 0.81083, \alpha_{f_2} = 1$

The pitch actuator long-term operation may lead to an actuator fault, modelled as an additive bias β_{bias}. Indeed, this fault deviates the desired pitch actuator β to $\beta + \beta_{bias}$. Also, the dynamic changes can be considered as a convex function of normal natural frequency and normal damping ratio. So, the pitch actuator (5) including the dynamic change and bias can be rewritten as,

$$\ddot{\beta} = -\omega_{n,N}^2(\beta + \beta_{bias}) - 2\omega_{n,N}\xi_N\dot{\beta} + \omega_{n,N}^2\beta_{ref} + \Delta\tilde{f}_{PAD}, \quad (6)$$

where, $\Delta\tilde{f}_{PAD} = -\alpha_{f_1}\Delta(\tilde{\omega}_n^2)\beta - 2\alpha_{f_2}\Delta(\tilde{\omega}_n\tilde{\xi})\dot{\beta} + \alpha_{f_1}\Delta(\tilde{\omega}_n^2)\beta_{ref}$, $\Delta(\tilde{\omega}_n^2) = \omega_{n,HL}^2 - \omega_{n,N}^2$ and $\Delta(\tilde{\omega}_n\tilde{\xi}) = \omega_{n,HAC}\xi_{HAC} - \omega_{n,N}\xi_N$.

Remark 1: The hydraulic pitch actuator has fast response time, large control effort (torque), and convenient centralization [34]. The electrical servo motor is another type of pitch actuator, to avoid the frequent hydraulic pitch actuator oil leakage and maintenance. Also, this type has more efficient and quicker response time than the hydraulic one [35]. However, this type of pitch actuator may suffer from overheated motor, cooling fan errors, brake damage, jams in the bearing and short circuits of the winding. Also, the battery system failure is considerable when the charger is not available [36]. In this case, the battery cannot provide enough power to pitch the blades. The electrical pitch actuator can be represented as a first order system as $\dot{\beta}(t) = -a_\beta\beta(t) + a_\beta\beta_{ref}(t)$, where $a_\beta = 1/\tau_\beta$ and τ_β is the pitch actuator time constant [1, 37]. For example, τ_β is selected as $50\,ms$ in [38], which is obviously negligible compared to the slow mechanical response of wind turbines. The mentioned electrical pitch actuator failures can be augmented in this equation as dynamic change, i.e. change in time constant $\Delta\tau_\beta$ and pitch angle offset f_β, as, $\dot{\beta}(t) = -a_\beta(\beta(t) + f_\beta) + a_\beta\beta_{ref}(t) + \Delta\tilde{f}_{PAD}(t)$, where, $\Delta\tilde{f}_{PAD}(t) = -\Delta a_\beta(\beta(t) + f_\beta) + \Delta a_\beta\beta_{ref}(t)$ and $\Delta a_\beta = -\Delta\tau_\beta/(\tau_\beta{}^2 + \tau_\beta.\Delta\tau_\beta)$. It should be pointed out that both the hydraulic and electrical pitch actuators can be represented as a first or second order system, though in practice, both are often represented as a second order system. Consequently, the electromechanical pitch actuator can be considered as fourth order system; two modes for the electric part, and two modes for the mechanical one [39]. Moreover, as the blade inertia is contributing in the mechanical mode, for the wind turbines with large blades, the dynamics of the mechanical part are dominant. So, the system can be approximated as a second order model. For this second order model, the natural frequency and damping ratio are $\omega_n = 11.11\ (rad/s)$ and $\xi = 0.6$, respectively. However, it is stated that for electromechanical pitch systems, which are more widespread in use, a first-order delay model may be sufficient [37, 39].

The generator converts shaft kinetic energy into electrical energy. Doubly-Fed Induction Generators (DFIG) are one of the most commonly used generator configurations [30]. In modern wind turbines, the frequency of produced electricity is adjusted by current control via a converter to enable variable speed operation [33]. Indeed, the converter acts as an interface between the generator and the grid. The converter is modelled as a first-order system with time delay τ_g to track the requested generator torque load $T_{g,ref}$ as,

$$\dot{T}_g = -a_g T_g + a_g T_{g,ref}, \quad (7)$$

where, $a_g = 1/\tau_g$ and T_g refers to generator shaft torque. The wind turbine internal electronic controller is much faster than the slow mechanical dynamic behavior. Accordingly, the produced electrical power in the generator P_g is approximated as a static relation as $P_g = \eta_g\omega_g T_g$ where η_g is the generator efficiency. Achievable generator torque and its variation, are considered to be limited as, $\dot{T}_{g,min} \le \dot{T}_g \le \dot{T}_{g,max}, T_{g,min} \le T_g \le T_{g,max}$ [33]. Internal electric faults in the converter, manufacturing defects and initialization of the converter controller, lead to either generator torque offset f_{T_g} or increased converter delay $\Delta\tau_g$ [20, 21, 40]. Although, the converter controller would typically be able to detect and accommodate $\Delta\tau_g$. So, the converter model (7) is rewritten as,

$$\dot{T}_g = -a_g(T_g + f_{T_g}) + a_g T_{g,ref} + \Delta\tilde{f}_{GC}, \quad (8)$$

where, $\Delta\tilde{f}_{GC} = -\Delta a_g(T_g + f_{T_g}) + \Delta a_g T_{g,ref}$ and $\Delta a_g = -\Delta\tau_g/(\tau_g^2 + \tau_g.\Delta\tau_g)$.

The main available wind turbine measurements are rotor speed, generator speed, pitch angle and generator torque. All measurements are assumed to contain unavoidable random noise [21]. Different sensor technologies are typically

adopted on wind turbines, e.g. strain gauge, piezoelectric, encoder, optical and laser sensors [10]. As most of the control schemes are designed based on the feedback of sensor measurements, sensor noise and faults lead to performance degradation or even instability. Lightning, moisture, salt spray and corrosion, may cause sensor faults. Also, blade misalignment at the installation step or during operation, leads to pitch sensor faults. Also, if the encoder is used for shaft speed estimation, loss of metal pieces on the shaft leads to inaccurately measured speed. Moreover, malfunctions of the electrical components of the encoders represent another reported source of faults [21]. On the other hand gearbox resonance frequency content on the generator speed sensor may deviate the sensor output from accurate readings [41]. In the modern wind turbines, to fulfill the physical redundancy concept, i.e. the most reliable configuration for FDI, the pitch angle, rotor speed and generator speed are measured with two separate identical sensors [42]. The sensor faults can be modelled as different fault types as, additive constant bias, gained multiplicative measurement, fixed and no sensor outputs. The measurement of variable X including sensor fault and noise content is given as, $X_s = X + \nu_X + X_{bias}$, where X_s is the measured signal, ν_X is random noise content and X_{bias} is the additive time variable bias, to take other sensor fault types into consideration. This fulfils the nonlinear description of wind turbine models associated with different fault sources. The considered faults in the wind turbine model are summarized in Table 4, in which the fault characteristics are stated.

2.2. Linearized model associated with faults

The aerodynamic behavior of wind turbines is a highly nonlinear function of blade pitch angle, wind speed and rotor speed, as (1). So, the nonlinear wind turbine model, i.e. (2), (4), (6) and (8), is usually linearized around different operation points. Considering the desired operation trajectory as $\overline{OP} = (\bar{V}_r, \bar{\beta}, \bar{\omega}_r)$, the linear aerodynamic behavior is represented via the linearization of (2) as,

$$T_a = T_{a,V_r}\tilde{V}_r + \frac{1}{3}\sum_{i=1}^{3} T_{a,\beta i}\tilde{\beta}_i + T_{a,\omega_r}\tilde{\omega}_r, \quad (9)$$

where, $T_{a,V_r} = (\partial T_a/\partial V_r)|_{\overline{OP}}$, $T_{a,\beta i} = (\partial T_a/\partial \beta_i)|_{\overline{OP}}$, $T_{a,\omega_r} = (\partial T_a/\partial \omega_r)|_{\overline{OP}}$, $\tilde{V}_r = V_r - \bar{V}_r$, $\tilde{\beta}_i = \beta_i - \bar{\beta}$ and $\tilde{\omega}_r = \omega_r - \bar{\omega}_r$. Now, the linearized wind turbine model including all considered faults, is summarized as,

$$\dot{\boldsymbol{x}} = A\boldsymbol{x} + B\boldsymbol{u} + F_a\boldsymbol{f_a} + \boldsymbol{R}V_r, \quad (10)$$

where, $\boldsymbol{x} = [\omega_r, \omega_g, \theta_\Delta, T_g, \beta_1, \dot{\beta}_1, \beta_2, \dot{\beta}_2, \beta_3, \dot{\beta}_3]^T$, $\boldsymbol{u} = [T_{g,ref}, \beta_{ref,1}, \beta_{ref,2}, \beta_{ref,3}]^T$, $\boldsymbol{f_a} = [\Delta f_{1,DT}, \Delta f_{2,DT}, \Delta f_{GC}, \Delta f_{PAD,1}, \Delta f_{PAD,2}, \Delta f_{PAD,3}]^T$, $\boldsymbol{R} = [T_{a,V_r}/J_r, 0,0,0,0,0,0,0,0,0]^T$, where, $\Delta f_{1,DT} = -\Delta B_{dt}\omega_r/J_r + \Delta B_{dt}\omega_g/J_r N_g - \Delta K_{dt}\theta_\Delta/J_r$, $\Delta f_{2,DT} = \eta_{dt}\Delta B_{dt}\omega_r/N_g J_g - \eta_{dt}\Delta B_{dt}\omega_g/J_g N_g^2 + \eta_{dt}\Delta K_{dt}\theta_\Delta/N_g J_g$, $\Delta f_{GC} = -a_g f_{T_g} + \Delta\tilde{f}_{GC}$, $\Delta f_{PAD,i} = -\omega_{n,N}^2\beta_{bias,i} + \Delta\tilde{f}_{PAD,i}$, $\Delta\tilde{f}_{PAD,i} = -\alpha_{f_1}\Delta(\tilde{\omega}_n^2)\beta_i - 2\alpha_{f_2}\Delta(\tilde{\omega}_n\tilde{\xi})\dot{\beta}_i + \alpha_{f_1}\Delta(\tilde{\omega}_n^2)\beta_{ref,i}$. $\beta_{bias,i}$ and $\beta_{ref,i}$ are pitch actuator bias and reference pitch angle of i^{th} blade, respectively.

Table 4. The wind turbines fault characteristics.

Components	Symptom	Category	Consequence	Severity	Deviation Time	Symbol	Fault model
Pitch sensor	Biased, gained, fixed and no measurement output	Sensor fault	Poor power optimization in low wind speed and power regulation in high wind speed.	Low	Medium	$\beta_{i,s,j,bias}$	Time variable additive bias
Rotor sensor						$\omega_{r,s,j,bias}$	
Generator sensor						$\omega_{g,s,j,bias}$	
Generator/ Converter	Offset generator torque bias	Actuator fault	Non-optimum power production.	Medium	Fast	f_{T_g}	Additive constant offset
Pitch actuator	Pitch angle bias		Poor power regulation, uneven aerodynamic torque and excited structural modes.			$\beta_{bias,i}$	
Generator/ Converter	Increased time delay	System fault	Slow generator torque control and non-optimal power production.	High	Fast	$\Delta\tau_g$	Added time delay
Pitch actuator	Pump Wear		Slow pitch angle adjustment and consequently poor power regulation.	High	Medium	$\Delta\tilde{f}_{PAD}$	Change in natural frequency and damping ratio
Pitch actuator	High air content in oil			Medium	Slow		
Pitch actuator	Hydraulic leakage			High	Medium		

Drivetrain	Wear and tear		Increased vibrations of drivetrain.	Medium	Very slow	ΔK_{dt} and ΔB_{dt}	Change in stiffness and damping
Blade aerodynamics	Debris build up		Out of designed aerodynamic relation (Non-optimal power production, poor power regulation).	Medium	Very slow	ΔC_p and ΔC_q	Aerodynamic coefficients change

Also, $A = \begin{bmatrix} A_{DT} & A_{GI} & A_{AE} \\ \mathbf{0}_{1\times3} & A_{GS} & \mathbf{0}_{1\times6} \\ \mathbf{0}_{6\times3} & \mathbf{0}_{6\times1} & A_{PS} \end{bmatrix}$, $A_{DT} = \begin{bmatrix} A_{DT11} & A_{DT12} & A_{DT13} \\ A_{DT21} & A_{DT22} & A_{DT23} \\ 1 & A_{DT32} & 0 \end{bmatrix}$, $A_{GI} = [0 \quad -1/J_g \quad 0]^T$, $A_{AE} = \begin{bmatrix} T_{a,\beta1}/3J_r & 0 & T_{a,\beta2}/3J_r & 0 & T_{a,\beta3}/3J_r & 0 \\ \multicolumn{6}{c}{\mathbf{0}_{2\times6}} \end{bmatrix}$, $A_{GS} = -a_g$, $A_{DT11} = -(B_r + B_{dt})/J_r + T_{a,\omega_r}/J_r$, $A_{DT12} = B_{dt}/J_r N_g$, $A_{DT13} = -K_{dt}/J_r$, $A_{DT21} = \eta_{dt} B_{dt}/N_g J_g$, $A_{DT22} = -B_g/J_g - \eta_{dt} B_{dt}/J_g {N_g}^2$, $A_{DT23} = \eta_{dt} K_{dt}/N_g J_g$, $A_{DT32} = -1/N_g$, $A_{PS} = \begin{bmatrix} A_{PS1} & \mathbf{0}_{2\times2} & \mathbf{0}_{2\times2} \\ \mathbf{0}_{2\times2} & A_{PS2} & \mathbf{0}_{2\times2} \\ \mathbf{0}_{2\times2} & \mathbf{0}_{2\times2} & A_{PS3} \end{bmatrix}$, $A_{PS1} = A_{PS2} = A_{PS3} = \begin{bmatrix} 0 & 1 \\ -\omega_{n,N}^2 & -2\xi_N \omega_{n,N} \end{bmatrix}$, $B = \begin{bmatrix} \mathbf{0}_{3\times1} & \mathbf{0}_{5\times1} & \mathbf{0}_{7\times1} & \mathbf{0}_{7\times1} \\ a_g & \omega_{n,N}^2 & \omega_{n,N}^2 & \mathbf{0}_{2\times1} \\ \mathbf{0}_{6\times1} & \mathbf{0}_{4\times1} & \mathbf{0}_{2\times1} & \omega_{n,N}^2 \end{bmatrix}$, $F_a = \begin{bmatrix} 1 & \mathbf{0}_{1\times2} & \mathbf{0}_{5\times2} & \mathbf{0}_{2\times1} \\ \mathbf{0}_{7\times1} & F_{a1} & F_{a1} & \mathbf{0}_{7\times1} \\ \mathbf{0}_{2\times1} & \mathbf{0}_{6\times2} & \mathbf{0}_{2\times2} & 1 \end{bmatrix}$ and $F_{a1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}^T$. The measurement model of the wind turbine including possible sensor faults and noise contents is written as,

$$\boldsymbol{y} = C\boldsymbol{x} + F_s \boldsymbol{f_s} + \boldsymbol{D}, \tag{11}$$

where, $\boldsymbol{y} = [\omega_{r,s,1}, \omega_{r,s,2}, \omega_{g,s,1}, \omega_{g,s,2}, T_{g,s}, \beta_{1,s,1}, \beta_{1,s,2}, \beta_{2,s,1}, \beta_{2,s,2}, \beta_{3,s,1}, \beta_{3,s,2}]^T$, $\boldsymbol{f_s} = [\omega_{r,s,1,bias}, \omega_{r,s,2,bias}, \omega_{g,s,1,bias}, \omega_{g,s,2,bias}, T_{g,bias}, \beta_{1,s,1,bias}, \beta_{1,s,2,bias}, \beta_{2,s,1,bias}, \beta_{2,s,2,bias}, \beta_{3,s,1,bias}, \beta_{3,s,2,bias}]^T$, $F_s = \boldsymbol{I}_{11\times11}$, $\boldsymbol{D} = [\nu_{\omega_{r,1}}, \nu_{\omega_{r.2}}, \nu_{\omega_{g,1}}, \nu_{\omega_{g,2}}, \nu_{T_g}, \nu_{\beta,1,1}, \nu_{\beta,1,2}, \nu_{\beta,2,1}, \nu_{\beta,2,2}, \nu_{\beta,3,1}, \nu_{\beta,3,2}]^T$, where, $\omega_{r,s,j}$, $\omega_{g,s,j}$ are the j^{th} measurement of rotor and generator speeds, respectively, and $\beta_{i,s,j}$ is the j^{th} measurement of the i^{th} pitch angle. $\omega_{r,s,j,bias}$ and $\omega_{g,s,j,bias}$ are time variable sensor biases of the j^{th} measurement of rotor and generator speeds, respectively. $T_{g,bias}$ is the generator torque sensor time variable bias. $\beta_{i,s,j,bias}$ is the time variable pitch bias of the j^{th} measurement of the i^{th} pitch angle. $\nu_{\omega_{r,j}}$ and $\nu_{\omega_{g,j}}$ refer to the noise content of the j^{th} measurement of the rotor and generator speeds, respectively. ν_{T_g} is the noise content of the generator torque sensor. $\nu_{\beta,i,j}$ is the noise content of the j^{th} sensor of the i^{th} pitch angle. Also, $C = \begin{bmatrix} C_1 & \mathbf{0}_{1\times2} & \mathbf{0}_{3\times1} & \mathbf{0}_{4\times2} & \mathbf{0}_{6\times2} & \mathbf{0}_{8\times2} \\ \mathbf{0}_{1\times2} & C_1 & 1 & C_1 & C_1 & C_1 \\ \mathbf{0}_{8\times2} & \mathbf{0}_{8\times2} & \mathbf{0}_{6\times1} & \mathbf{0}_{5\times2} & \mathbf{0}_{3\times2} & \mathbf{0}_{1\times2} \end{bmatrix}^T$, where, $C_1 = [1 \quad 1]$. It is obvious that the redundancy concept is achieved for rotor speed, generator speed and pitch angle sensors with two identical sensors.

2.3. Linear parameter varying modelling

The LPV wind turbine modeling framework has emerged in the last decade [43], in which, the wind turbine model is linearized around several operational points. Accordingly, a set of linearized models is adopted and, according to the estimated operational point, the proper model is chosen. Indeed, in (2), as wind speed varies, T_a is also variable, which leads to variation of the matrix A in (10). So, for different wind speeds, different linearized models are obtained. Consequently, having all possible linearized models as the feasible dynamic descriptor set, leads to the LPV wind turbine model representation. This provides proper design freedom to achieve robust FDI performance [33, 44]. Considering (10) and for the operation point $OP(k) = \big(V_r(k), \beta(k), \omega_r(k)\big)$, the overall LPV wind turbine model is stated as,

$$\dot{\boldsymbol{x}} = A(\theta)\boldsymbol{x} + B\boldsymbol{u} + F_a \boldsymbol{f_a} + \boldsymbol{R}(\theta)V_r, \tag{12}$$

where, $A(\theta) = \begin{bmatrix} A_{DT}(\theta) & A_{GI} & A_{AE}(\theta) \\ \mathbf{0}_{1\times3} & A_{GS} & \mathbf{0}_{1\times6} \\ \mathbf{0}_{6\times3} & \mathbf{0}_{6\times1} & A_{PS} \end{bmatrix}$, $A_{DT}(\theta) = \begin{bmatrix} A_{DT11}(\theta) & A_{DT12} & A_{DT13} \\ A_{DT21} & A_{DT22} & A_{DT23} \\ 1 & A_{DT32} & 0 \end{bmatrix}$, $A_{DT11}(\theta) = -(B_r + B_{dt})/J_r + \big(T_{a,\omega_r}/J_r\big)\big|_\theta$, $A_{AE}(\theta) = \begin{bmatrix} T_{a,\beta1}/3J_r\big|_\theta & 0 & T_{a,\beta2}/3J_r\big|_\theta & 0 & T_{a,\beta3}/3J_r\big|_\theta & 0 \\ \multicolumn{6}{c}{\mathbf{0}_{2\times6}} \end{bmatrix}$ and $\boldsymbol{R}(\theta) = [T_{a,V_r}/J_r\big|_\theta, 0,0,0,0,0,0,0,0,0]^T$. θ is the set of all possible operating points such that $\theta \in \Theta_k$ and $\Theta_k = \{OP(k) \in \mathbb{R}^3 | OP_{min} \leq \|OP(k)\| \leq OP_{max}\}$, where $\|\chi\|$ represents a properly-selected norm operator on variable χ. Indeed, it

is assumed that the operational points are bounded. The model (12) includes k linearized models. It should be noted that the measurement equation is the same as (11). In (12), $\hat{\theta}$, i.e. the estimation of operating point θ, is needed to accurately implement the LPV representation of the wind turbine.

2.4. Fuzzy Takagi–Sugeno modelling

In this approach, using multiple linearized models, fuzzy *if-then* rules are defined based on the expert's knowledge which combine all the linear models utilizing the T-S prototype [45-49]. The wind turbine measurements can be used to estimate fuzzy T-S prototype parameters [50]. The fuzzy variable vector $\boldsymbol{Z}$ is defined as, $\boldsymbol{Z}(t) = [\omega_r, \beta, V_r]$. Assume q fuzzy rules are defined as, *if* ω_r *is* M_{1i} *and* β *is* M_{2i} *and* V_r *is* M_{3i}, *then* $\dot{\boldsymbol{x}} = A_i\boldsymbol{x} + B\boldsymbol{u} + F_a\boldsymbol{f_a} + \boldsymbol{R}_i$, for $i = 1, \dots, q$. M_{li} are fuzzy membership functions for $l = 1,2,3$. Also, A_i and $\boldsymbol{R}_i$ are the expert-defined dynamic system matrix and disturbance vector, respectively. The complete fuzzy T-S wind turbine model is represented as,

$$\dot{\boldsymbol{x}} = \sum_{i=1}^{q} \mu_i\big(\boldsymbol{Z}(t)\big)\,(A_i\boldsymbol{x} + B\boldsymbol{u} + F_a\boldsymbol{f_a} + \boldsymbol{R}_i V_r), \tag{13}$$

where, $\mu_i\big(\boldsymbol{Z}(t)\big) = h_i\big(\boldsymbol{Z}(t)\big) / \sum_{i=1}^{q} h_i\big(\boldsymbol{Z}(t)\big)$ and $h_i\big(\boldsymbol{Z}(t)\big) = \prod_{l=1}^{3} M_{li}\big(\boldsymbol{Z}(t)\big)$. The measurement equation is the same as (11). In (13), the expert's knowledge plays a vital role to properly define the fuzzy rules, dynamic matrix A_i and disturbance vector $\boldsymbol{R}_i$. Otherwise, the designed model is not able to represent the wind turbine dynamic response.

3. Fault detection methods applied to wind turbines

FDI can be utilized as a fully/partly automatic scheme to detect and locate the possibly occurring faults on the wind turbine to optimize the required maintenance procedures, reduce downtime, and to avoid catastrophic failure. The modern maintenance strategies aim to reduce human intervention by implementing hardware or software redundancy on the wind turbines to automatically detect the faults based on the collected and analyzed data and, consequently, to reduce/remove the fault effects.

Hardware redundancy involves equipping the components such as sensors and actuators, with physically identical counterparts to generate so-called residual signatures which contain the possible fault information. This approach increases the weight, occupied space, data acquisition complexity and, consequently, final design cost. These issues are very problematic for offshore wind turbines. In contrast, software redundancy or computer-based FDI techniques have been developed on wind turbines during the last decade to overcome the aforementioned problems [51], in which the mathematical model of the wind turbine is used to generate the redundant signals and, accordingly, residuals.

It should be pointed out that there exist other faults in the wind turbine structure which are not mentioned in Table 4. For instance, degradation of drivetrain lubrication oil which leads to high bearing temperature and, consequently, lubrication oil ageing. Also, due to wind gusts and consequent temporary misalignment of rotor and generator shafts, the bearings and gears are damaged [52]. Blade cracks, bearing wear and spalls, gear teeth cracks, generator winding damage and overheating, are some other reported wind turbine faults. Condition monitoring methods based on Supervisory Control and Data Acquisition (SCADA), structural health monitoring techniques, frequency spectrum analysis and vibration signal processing are the main approaches to detect these aforementioned faults [53-55]. Fourier transformation analysis [56], wavelet methods [57], manifold learning [58], support vector machines [47, 59, 60], vibration-based condition analysis [57], thermography, strain measurements and acoustic monitoring [18, 61] are some examples of condition monitoring. All these methods can be categorized as signal-based (or data-driven) fault detection and there are rich reviews on applying these methods on wind turbines [18, 52, 54, 62-66], so these methods are not repeated here. On the other hand, yaw actuator faults, whether actuator malfunction or a stuck brake is not considered, because the yaw mechanism is mostly considered as an on/off actuator and, accordingly, inactive [40].

The most challenging issue, which should be considered in wind turbine FDI schemes, is that the wind speed is poorly measured by the anemometer due to spatial/temporal effective wind speed distribution over the blade plane, turbulence, wind shear and tower shadow effects. So, wind speed is considered as an unknown disturbance as well as consequent aerodynamic torque. Also, FDI schemes should be robust against the considerable noise content of sensor measurements [67]. In this section, the wind turbine model-based FDI techniques are reviewed. Also, to have a comprehensive and fruitful review, the FDI methods are categorized systematically, which are summarized in Figure 4.

3.1. Residual-based approach

The residual-based design represents one of the most common wind turbine FDI techniques to detect different faults. This approach relies on the residual signal obtained by comparing the wind turbine output and the corresponding duplicated one, which carries any probable fault information. In model-based residual generation, despite physical redundancy techniques, the redundant measurements can be obtained via the wind turbine mathematical models (see Section 2), or via design of an appropriate observer. Finally, by adopting an appropriate residual signal evaluation, the fault is detected [68]. The most commonly adopted residual-based FDI techniques for wind turbines are the parity relation method [69] and observer design [70]. Generally, the residual vector is defined as,

$$\boldsymbol{d} = \boldsymbol{y}_m - \boldsymbol{y}_w, \tag{14}$$

where, $\boldsymbol{y}_m$ is the wind turbine output vector and $\boldsymbol{y}_w$ is the wind turbine duplicated output vector. In (14), for the sake of consideration, the vector $\boldsymbol{d}$ contains all sensors and duplicated output information. Although, it can be constructed for one sensor to reduce complexity of the residual evaluation.

The widely-exploited residual evaluation methods are simple geometric logic (e.g. threshold check), statistical scheme (e.g. statistical feature extraction), and Bayesian approaches. In the first approach, an adaptive or fixed threshold σ_{th} is selected, from which if $\boldsymbol{d}$ violates, the faults are detected [71]. Indeed, if $\|\boldsymbol{d}\| > \sigma_{th}$, then the fault is detected, otherwise no fault has occurred. It should be noted that the presence of measurement errors, disturbance and uncertainty, may lead to false fault detection. Indeed, these effects may cause $\boldsymbol{d}$ to be greater than σ_{th}, when no fault has occurred [72]. Also, by selecting too large a σ_{th}, to avoid false detection, some faults with small effect on $\boldsymbol{d}$ are not detected, which may yet cause major operational deficiency, leading to the missed detection problem. So, statistical analysis of the residual signal can be considered to provide more accurate residual evaluation. Generalized likelihood ratio test, cumulative variance index and the use of up and down counters, are some statistical analysis methods. These methods are available e.g. in [51, 73]. The Bayesian approach for residual evaluation will be outlined in Section 3-5.

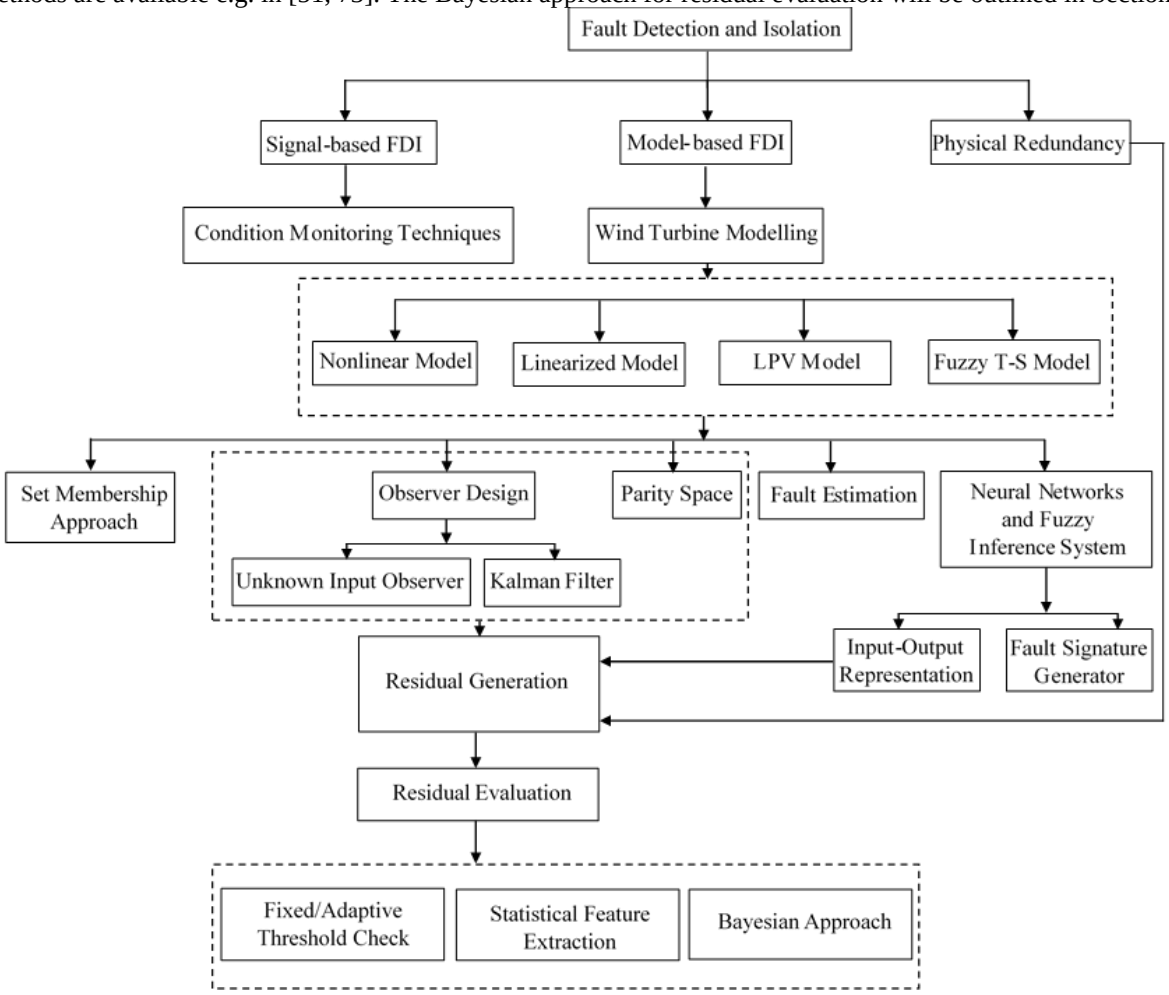

Fig. 4. FDI methods applied on wind turbines.

3.1.1. Parity space approach

The parity residual generation approach can be adopted on the whole or a single part of the wind turbine to achieve the FDI task. This approach uses the mathematical model of the wind turbine presented in Section 2. This model is fed with the same inputs as the wind turbine. In the fault-free case, both the wind turbine and the model, generate the same outputs. Accordingly, by comparing these two outputs the residual signal is constructed, which deviates considerably from zero in the case of fault occurrence. This approach is sketched in Figure 5 [69, 74]. As an example. in [75] the parity equations are utilized to detect and isolate faults in the blade pitch actuator and drivetrain. The highly nonlinear wind turbine dynamics and its variable operation points make a high-fidelity description of the whole wind turbine behavior difficult. Also, the design of different models for each subsystem may increase the complexity of the

final scheme. Also, the wind speed is not accurately measurable. Figure 5 highlights that the wind speed is one input to the wind turbine, which should be identically fed to the model. So, the wind speed should be either accurately measured or estimated. Different measurement or estimation of wind speed approaches have been reviewed in [76]. On the other hand, in the case of offshore wind turbines, the unmeasurable sensor noise and environmental disturbance are considerable and inevitable. So, in [75] an appropriate filter was designed to make the residual robust against noise and disturbances, while yet being sensitive to the considered faults. Also, in [77] an adaptive threshold is designed to accurately evaluate the constructed residual signal of the wind turbine to eliminate false detection due to noise content on the residual.

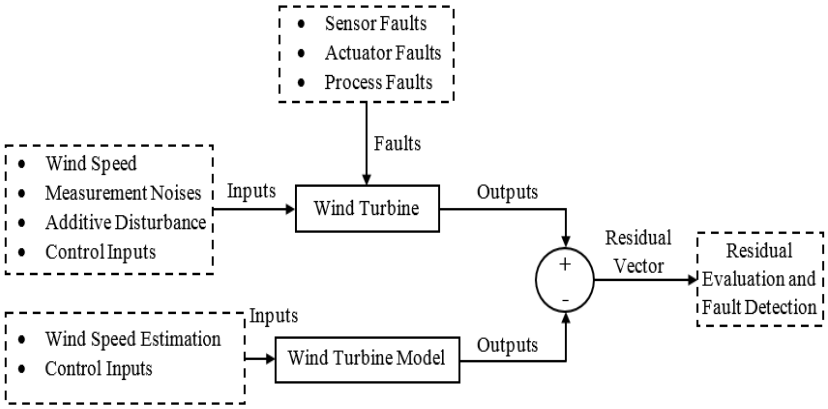

Fig. 5. Parity based residual generation approach.

3.1.2. Observer design approach

The most accurate residual generator is obtained by means of an appropriate fault diagnosis observer. Indeed, this approach relies on residual signals that are decoupled from the unknown inputs, whether wind speed, noises or other uncertainty effects [10]. In contrast to the parity approach, in the observer design, the observation error is fed back into the dynamic system to reduce the error, adopting a proper observation gain. Consequently, using the observed states, the residual signal is constructed. The observer is designed for the fault-free model. So, considering (10), the observer dynamic system is defined as,

$$\begin{aligned} \dot{\hat{\boldsymbol{x}}} &= A\hat{\boldsymbol{x}} + B\boldsymbol{u} + \boldsymbol{R}\hat{V}_r + \boldsymbol{H}\boldsymbol{e}, \\ \hat{\boldsymbol{y}} &= C\hat{\boldsymbol{x}}, \\ \boldsymbol{e} &= \boldsymbol{y} - \hat{\boldsymbol{y}}, \end{aligned} \tag{15}$$

where, $\hat{\boldsymbol{x}}$ is the estimated wind turbine states vector, $\hat{V}_r$ is estimated wind speed, $\hat{\boldsymbol{y}}$ is estimated outputs vector, $\boldsymbol{e}$ is observation error and $\boldsymbol{H}$ is the observer gain matrix. The only condition for the design of the observer is that the considered wind turbine model (or a part of it) must be observable, i.e. $rank([C\ CA\ \dots CA^{n-1}]^T) = n$, where $n = length(\boldsymbol{x})$. If the $\boldsymbol{H}$ is designed properly, $\boldsymbol{e}$ converges to zero. This approach is depicted in Figure 6, where the estimation of wind speed, i.e. $\hat{V}_r$ is still required.

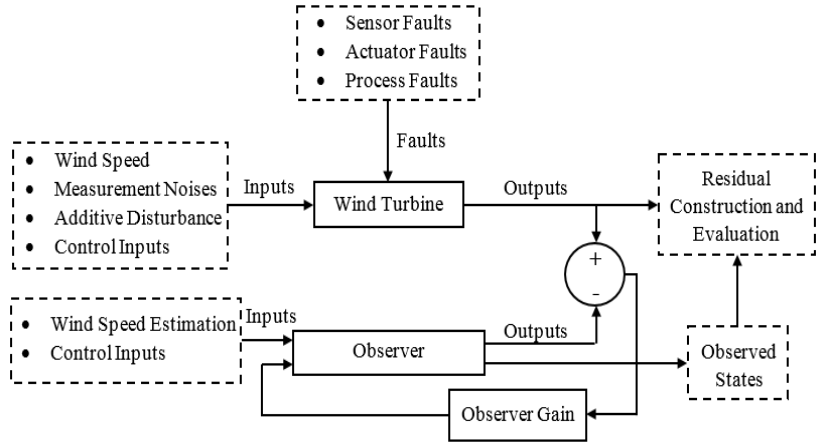

Fig. 6. Observer based residual generation approach.

The wind turbine observer design mostly includes various types of Kalman filter [51, 78, 79] and unknown input observer (UIO) schemes [70, 80]. For example, using the Kalman filter, as the optimal observer, the reduction of wind

turbine sensor noise on the observed states, is optimally guaranteed [51, 78, 79, 81]. The main disadvantage of the observer based FDI methods is that the whole linearized wind turbine model should be used to take advantage of well-developed linear observer design theories [3]. Recently the sliding mode observer has shown interesting results to be implemented on the whole nonlinear model of the wind turbine [82, 83]. In [84] the observer design is conducted on the wind turbine LPV model, which shows acceptable FDI performance for different fault scenarios. In [3], an extended observer on the wind turbine LVP model was designed to estimate system states and fault signals simultaneously. Also, via H_∞ optimization the robustness of the observer is improved against additive disturbances. Similarly, in [51], for disturbance decoupling and, meanwhile, to generate the optimal residual signal with respect to sensor noise, the Kalman filter is augmented with observers. A bank of several observers was proposed in [85], each of them being sensitive to only one fault and robust against the other faults. So, via the fault signature analysis, the fault detection as well as isolation are achieved at the same time. In [79] the performance of the Kalman filter, bank of observers and parity based residual generation are compared. It should be noted that in [27, 86] a new observer design scheme is proposed for wind turbine fault detection, known as interval observer design, for a set of valid models using the so-called set-membership approach.

UIO represents an improvement of the ordinary observer scheme to eliminate the need for wind speed estimation. In UIO, the observer dynamic system is totally decoupled from external unknown disturbances, i.e. wind speed, by adopting a proper observer structure, which is given as,

$$\begin{aligned} \dot{\hat{\boldsymbol{z}}} &= \boldsymbol{F}\boldsymbol{z} + \boldsymbol{T}\boldsymbol{B}\boldsymbol{u} + \boldsymbol{K}\boldsymbol{y}, \\ \hat{\boldsymbol{x}} &= \boldsymbol{z} + \boldsymbol{G}\boldsymbol{y}, \\ \hat{\boldsymbol{y}} &= C\hat{\boldsymbol{x}}, \end{aligned} \tag{16}$$

where, $\boldsymbol{z}$ is the observer states vector, $\boldsymbol{F}$, $\boldsymbol{T}$, $\boldsymbol{K}$and $\boldsymbol{G}$ are matrices to be designed for achieving the decoupling $\boldsymbol{R}$. Necessary and sufficient conditions for design of UIO are, $rank(C\boldsymbol{R}) = rank(\boldsymbol{R})$ and (C, A_1) is a detectable pair, where $A_1 = A - \boldsymbol{R}((C\boldsymbol{R})^T C\boldsymbol{R})^{-1}(C\boldsymbol{R})^T CA$. In this scheme, the disturbance effect on the residual signal is decoupled. In [70, 80], the wind turbine sensor faults are detected with the UIO based approach.

3.2. Fault estimation approach

This approach relies on a proper fault estimator that is used for fault detection purposes. Also, an estimator bank can be designed to isolate the faults affecting different wind turbine components [42]. Each estimator of the bank is designed for a specific fault. The general estimator structure can be represented as,

$$\dot{\hat{\boldsymbol{f}}} = g(\hat{\boldsymbol{f}}, \boldsymbol{y}, \boldsymbol{u}, \hat{V}_r), \tag{17}$$

where, $\hat{\boldsymbol{f}}$ is an estimated fault and g is a nonlinear function to be designed. Despite the observer approach, in the estimation techniques, the fault function is directly obtained. The main step in the estimator design is the selection of design parameters. Indeed, in the case of proper design parameter selection, the need for the threshold is eliminated [42]. In Figure 7, the fault estimation is illustrated schematically. The estimator structure is designed as a dynamic system or static estimator such as the least squares filter [3, 87]. It should be noted that considering the nonlinear dynamics of wind turbines and different sources of disturbance, adaptive filters are mainly addressed by the most recent studies [32, 82]. The advantage of the adaptive estimator concerns its robustness, which can be theoretically guaranteed. This feature leads to reduction in the false and missed detection rates [29, 88]. The most recent fault estimator designs exploit fuzzy sliding mode estimators, whose application for wind turbines FDI is addressed in [82, 89, 90].

3.3. Neural networks and fuzzy inference system approaches

Neural networks and fuzzy inference systems can be used for wind turbine FDI designs, and they are mainly divided into two different approaches, namely input-output representation and fault feature generators (classifiers), analyzed in the following sections.

3.3.1. Input-output representation

Neural networks provide one of the best tools to represent the nonlinear and partially known behaviour of wind turbines [48]. This approach is illustrated in Figure 8, in which the designed neural network is fed with the actual/estimated inputs, i.e. the same as the wind turbine, to generate the redundant outputs. It should be noted that the wind speed can be estimated in the neural network as well as the duplicated outputs [91, 92].

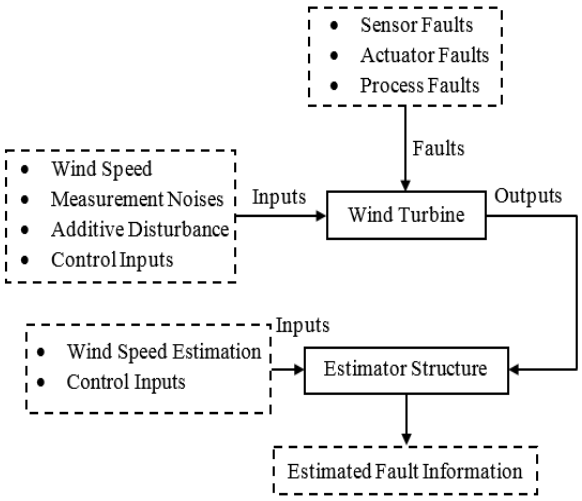

Fig. 7. Fault estimation diagram.

The multi-layer perceptron networks and radial basis function neural networks are the most commonly adopted structures for FDI purposes. The main step in this approach is the offline training to tune the neuron weights to the optimal ones. Adaptive neuro fuzzy interface system is an online fast learning adaptive training approach, which takes advantage of the neural network robustness, the learning and training capabilities, and the fuzzy inference system interpretability. In both offline and online schemes, a properly large dataset should be available as a-priori knowledge to train the network in the fault-free case. Accordingly, some works proposed a data-driven learning scheme [93]. The application of this approach on wind turbines FDI has recently been addressed in [94] and applied on different wind turbine components e.g. gearbox and generator faults [95, 96] and pitch faults [95].

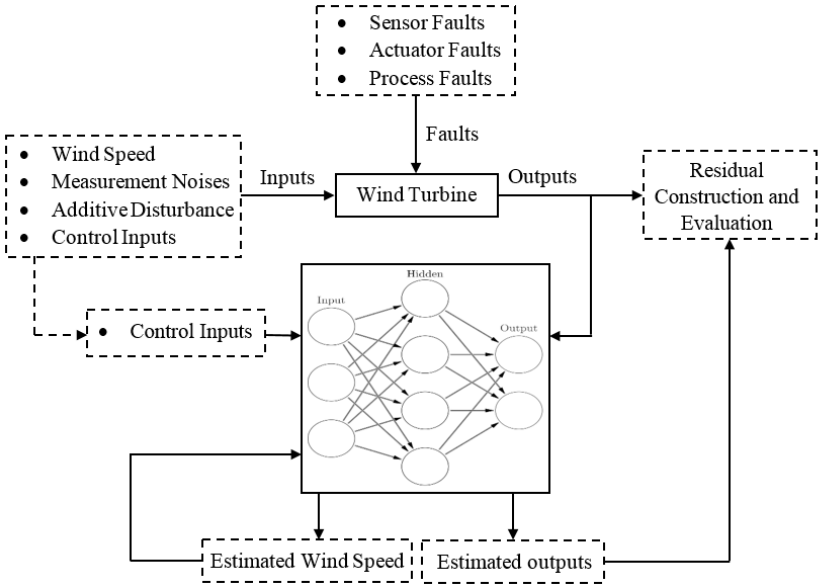

Fig. 8. Neural network input-output based FDI.

3.3.2. Fault signature generator

In contrast to the previous approach, the fault information can be directly extracted/inferred in this method, which relies on the design of an accurate a-priori knowledge-based network, e.g. Adaptive Neuro-Fuzzy Inference System (ANFIS) or Fuzzy Inference System (FIS), as illustrated in Figure 9. Accordingly, the expert knowledge is needed to be included in the design, whether as the numerical rules or fuzzy *if-then* linguistic rules. For example, the rule ‘‘*If generated power is high at low wind speed region, it may imply possible sensor fault*’’ can be used. These rules are also known as classifiers [97]. One of the advantages of fuzzy logic and fuzzy membership representation is that the uncertain measurement of the wind speed provided by the anemometer can be directly used [98]. In [99], classification methods are utilized for rotor imbalance/aerodynamic asymmetry fault detection.

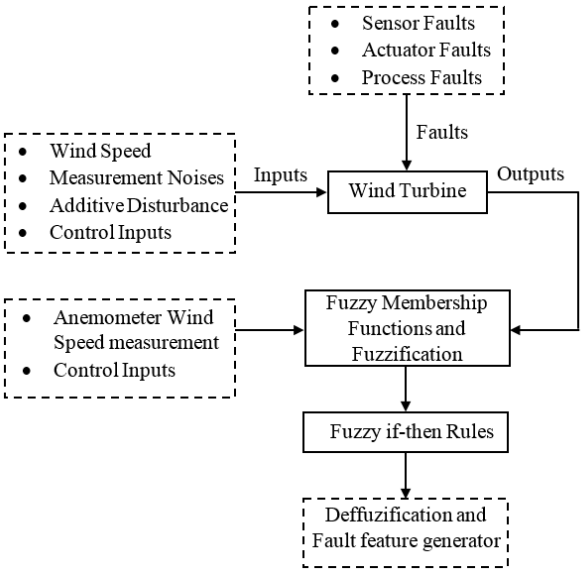

Fig. 9. Fuzzy fault feature generation diagram.

3.4. Set-membership approach

This scheme relies on a set of mathematical models of the wind turbine that are exploited for system consistency checking. Model uncertainties and noises are assumed to be unknowns, but with known upper and lower bounds. Due to unmodeled dynamics, noise and uncertainty of the wind turbine, the input/output data can be consistent with more than one model [100, 101]. So, an active model diagnosis is adopted in which, at each time step taking model falsification concepts into consideration, an auxiliary input signal is fed into both wind turbine and model sets, to find the correct model out of the predefined set. Then, the consistency of the current input/output data and the model is checked to detect the possible faults [71].

This method guarantees that the valid model of the wind turbine is never falsified. Additionally, the set-membership approach can be used only for one subsystem to check only one parameter, i.e. the feasible parameter set is defined instead of the valid model set [87, 102], assuming the wind speed and measurement noise are bounded as $|V_r| \leq V_{r,max}$ and $\boldsymbol{D} \in \bar{\boldsymbol{D}}$ in (10) and (11). Also, initial conditions can be given in a compact set $\boldsymbol{x}(0) \in \mathbf{X}_0$. In every iteration of the set-membership algorithm, a consistent set, $S^c(t)$ is defined which contains all the states that are consistent with the wind turbine model, considering $\mathbf{X}_0$, $V_{r,max}$ and $\bar{\boldsymbol{D}}$. The control input $\boldsymbol{u}$ can be used for FDI purposes, but here, to significantly excite the wind turbine, assume that an auxiliary input $\boldsymbol{u}^a(t)$ is applied to the wind turbine. The predicted set S^p at time step t can be defined as $S^p(t) = \{A\boldsymbol{x}(t-1) + B\boldsymbol{u}^a(t-1) + \boldsymbol{R}\hat{V}_r(t-1) | \boldsymbol{x}(t-1) \in S^c(t-1), \hat{V}_r(t-1) \leq V_{r,max}\}$. Also, the updated set S^u at time step t can be defined as $S^u(t) = \{\boldsymbol{x}(t) | C\boldsymbol{x}(t) \in \boldsymbol{y}(t) \oplus (-\bar{\boldsymbol{D}})\}$, where $\oplus$ denotes the Minkowski sum. Now the consistent set can be computed as $S^c(t) = S^p(t) \cap S^u(t)$. A fault can then be detected at time step t if the following relation holds true,

$$S^c(t) = \emptyset. \quad (18)$$

An advantage of the set-membership approach is that the need for thresholds is eliminated while the false alarm and missed alarm are avoided [86, 100]. The conservatism of this approach, because of uncertainty propagation and over-approximations required in the set computations, is the main drawback. This approach is illustrated in Figure 10. The combination of set-membership approach and observer design emerges as a new and promising approach for wind turbine FDI, as proposed in [27, 86].

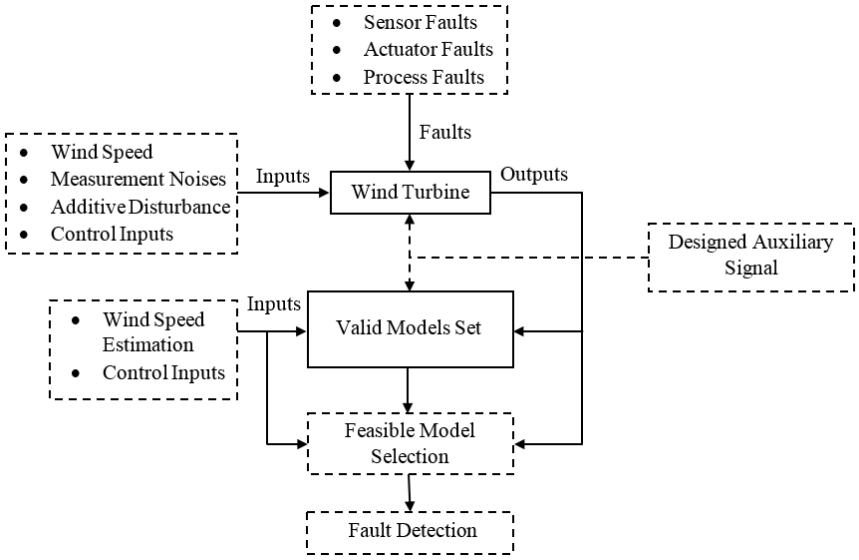

Fig. 10. Set-membership FDI approach.

3.5. Bayesian approach

This approach has recently been reformulated for model-based wind turbine FDI application [103], in contrast to its traditional application for signal-based condition monitoring. In this regard, in the Bayesian framework, the residual signal is evaluated to detect faults. By taking advantage of Bayesian reasoning, the expert knowledge about the wind turbine operation can be directly included in the FDI scheme [104]. Indeed, the residual evaluation is obtained as the fault probability extraction in the Bayesian framework as, $P(f|d,\hat{x},y)$ i.e. the conditional fault probability having residual, estimated state and output vectors [105]. Accordingly, the need for threshold evaluation is eliminated. Also, using the valid measurement, a fault occurrence can be predicted, by considering Bayesian fault probability, e.g. wind turbine bearing crack prediction [106]. A recent and promising approach for the wind turbine feasible parameter set determination is addressed in [104] where the set-membership FDI is reformulated in a Bayesian framework.

4. Application of Fault detection methods to wind turbine components

In this section, the methods that have been introduced in Section 3 are analyzed and discussed based on their application on wind turbine components. The aim is to critically review the methods to enable the readers to choose appropriate methods for further study.

4.1. Sensor fault detection

As the sensor outputs are mostly utilized in the feedback controller scheme, the required wind turbine performance may not be maintained due to a fault on the corresponding sensor [10]. Especially in the case of the offshore wind turbines operating in harsh environment, it is more likely that the sensor measurements are corrupted with faults [68]. The pitch sensor FDI is studied in [10], as the pitch angle control is a vital scheme for power regulation of wind turbines. The residual signal is generated using the physical redundant sensors and evaluated by considering mean and variance changes. In the parallel loop, the model-based pitch sensor is utilized to enable parity relation construction to isolate the detected fault. Indeed, it is aimed to identify which pitch sensor is faulty.

The application of the Kalman filter has been considered on wind turbine sensor FDI, in which it is guaranteed that the noise effect is minimized when proper conditions are satisfied. For example, in [68] the Kalman filter is designed for pitch sensor FDI. Similarly, in [51] the Kalman filter is used for the residual generation which is evaluated via the generalized likelihood ratio test to detect the pitch and drivetrain sensor faults, while the redundant sensor is needed for fault isolation. Also, the applied aerodynamic torque, i.e. T_a in (4), is considered as a disturbance and the designed Kalman filter has proven to be robust against wind speed variation.

The observer design has been analyzed in different modelling frameworks. For example in [44], the power sensor and generator speed sensors are considered and the observer is designed for the LPV wind turbine model, but the sensor noise is not considered. In [107, 108] *H-/H∞* optimization is addressed to minimize the noise effect on the designed FDI observer. In [3], the extended observer for the whole wind turbine model is designed in the LPV framework to estimate the states as well as faults at the same time for pitch and drivetrain sensor faults using the linear matrix inequality. So, this approach can be considered as an estimation method. Also, the wind speed is considered as an unknown disturbance and the proposed observer is insensitive to it. The fuzzy T-S framework has been considered in several papers to design the sensor FDI scheme. In [109] for low wind speed regions and in [29] for high wind speed

regions, the generator current sensor fault is detected via an observer design in the fuzzy T-S framework. Similarly, in [110], [111] and [112], the generator voltage sensor, pitch sensor and generator speed/power sensors, respectively, are considered and fuzzy T-S fault observers are designed.

Regarding the unknown wind speed variation, UIO design is an appropriate choice to remove the need for wind speed estimation, especially considering drivetrain sensor FDI designs [85]. In this approach, the wind speed variation is decoupled from the designed observer [80]. For example, in [70, 80, 113] UIO is designed for drivetrain sensor fault detection including rotor speed and generator speed sensors. Observer bank design is a suitable approach to detect and isolate the sensor faults, and at the same time, to achieve fault isolation with no need for physical redundant sensors. Each observer is designed to be sensitive only to one given fault and robust to other faults and disturbances. In [85], the UIO bank is designed for a set of sensor faults including rotor speed, generator speed and wind speed sensors. Finally, more accurate evaluation of the residual signal can be conducted with set-membership checks or Bayesian inferences. In [100], the pitch and rotor sensor faults are considered and, utilizing the set-membership approach, the need for threshold checking is removed and also, no positive false alarm is produced. In [103] the relationship between wind turbine failure root causes and symptoms are used with a Bayesian Network for pitch sensor fault detection, using SCADA data to reduce false alarms and missed fault rates. The available wind turbine sensor FDI methods associated with different fault sources, are analyzed comprehensively in Table 5.

Table 5. Wind turbines sensor FDI methods.

Fault Source	FDI Method	Reference	Advantage	Disadvantage
Pitch Sensor	Physical Redundancy/ Parity Equation	[10]	Accurate fault detection. No need for wind speed estimator.	Need for extra physical pitch sensors.
	Observer (H-/H∞ Optimization)	[108]	Noise effect reduction on residual.	Need for wind speed estimation. Complex and timely numerical algorithm.
	LPV Extended Observer	[3]	Estimation of the states as well as faults at the same time.	Sensitive to design parameters. Complex procedure for computer simulation.
	Kalman Filter Design	[51, 68]	Minimization of noise on residual.	Wind speed estimation. Complex and timely numerical algorithm. Need for an extra sensor for isolation.
	Fuzzy T-S Observer	[111]	More accurate wind turbine model. The reduction of modelling uncertainty on the fault detection.	The effective design of fuzzy rules and set-memberships.
	Set-Membership Approach	[100]	Threshold check is not needed. No positive false alarm is produced.	Wind speed estimation. Need for implementable and simplified numerical algorithm to calculate the valid models set.
	Bayesian Inference using SCADA data to generate fault symptoms	[103]	Reduced false alarm and missed fault rates.	Considerable sensor noise effect. Low sample rate of SCADA data.
Drivetrain Sensors	Kalman Filter Observer	[51]	Aerodynamic torque is considered as disturbance. Minimization of noise on residual.	Complex and timely numerical algorithm. Need for an extra sensor for isolation.
	LPV Extended Observer	[3]	Estimation of the states as well as faults at the same time. No need for wind speed estimation.	Sensitive to design parameters. Complex procedure on digital computer.
	UIO	[70, 80, 113]	One-step calculation design procedure.	Too simplified modelling assumptions in the design which make it less practical.
	UIO Bank	[85]	Fault detection and isolation at the same time.	
	Set-Membership Approach	[100]	Threshold check is not needed. No positive false alarm is produced. Less complex computational procedure.	Need for wind speed estimation.
Generator Voltage and Current Sensors	Observer	[114-116]	No need for any extra redundant sensor.	Effect of sensor noise content on the observation performance is not considered. Need for wind speed estimator.
	Fuzzy T-S Observer	[29, 109, 110, 112]	More accurate wind turbine model. The reduction of modelling uncertainty on the fault detection.	The effective design of fuzzy rules and set-memberships.
Power Sensor	Observer (H-/H∞ optimization)	[107]	Noise effect reduction on residual.	Wind speed estimation. Complex and timely numerical algorithm.
	LPV observer	[44]	Observer design for whole wind turbine.	No noise/disturbance consideration.

4.2. Pitch actuator fault detection

The power regulation of wind turbines is essential for high wind speed situations, i.e. to retain the generated power at nominal power, by adjusting the blade pitch angle to control the applied aerodynamic torque and consequently, rotor speed [34]. Also, in dangerous wind speed situations, it is aimed to feather the wind turbine by pitching the blades into the desired orientation to bring the wind turbine to a stop, to avoid mechanical brake engagement, which may induce considerable stress on the rotor shaft. So, the pitch actuator plays a vital role to accurately tune the blade pitch angle at β_{ref}. Accordingly, the pitch actuator faults lead to deviation of the pitch angle from β_{ref}. As the pitch actuator fault-free dynamic behavior (5) is represented as a linear and known relation, the parity equation can be used to generate the residual. As the measured pitch angle, to be used in the parity equation, is corrupted by measurement noise, in [117] the least square residual evaluation with sliding data window is exploited to evaluate the residual signal and detect $\Delta\tilde{f}_{PAD}$ while minimizing noise effects. On the other hand, $\Delta\tilde{f}_{PAD}$ can be considered as the model uncertainty and accordingly, in [75] the robust residual filtering and parity equations are combined to accurately detect the pitch actuator dynamic change for each blade. Also, the pitch sensor fault effect is distinguished from $\Delta\tilde{f}_{PAD}$, utilizing the fault-end-effect, i.e. fault signature.

The pitch sensor noise, dynamic change and bias are challenging effects to be separated at the same time, which motivates many recent studies, for which observer design is a potentially suitable approach. In [118] the Kalman filter observer is designed to detect the pitch actuator bias. Also, in [108], the *H-/H∞* optimization method is augmented in the observer design to generate the optimal residual, i.e. minimizing the noise effect. Regarding pitch sensor effects, in [84] an observer is designed with adaptive gains to detect dynamic change, distinguished from sensor noise and sensor faults. In a similar manner, in [32], the sliding mode observer is designed to detect dynamic change with an adaptive hierarchical method to facilitate the real-time implementation. In [82], the sliding mode observer is designed for the wind turbine fuzzy T-S model to detect any increased time delay in the electrical pitch actuator.

The application of soft computing using SCADA data to detect pitch actuator faults have shown promising results to avoid complicated FDI schemes. In [95] using neural networks, a pattern recognition structure was proposed to detect pitch actuator faults. On the other hand, in [94] the Bayesian fault probability was obtained to evaluate the SCADA alarm data and detect potential pitch actuator dynamic change. To this end, pitch actuator FDI methods are elaborated in Table 6.

Table 6. Pitch actuator FDI methods.

Fault Type	Fault Symbol in (6)	Fault Detection Method	Reference	Characteristic	Advantage	Disadvantage
Pitch Actuator Dynamic Change	$\Delta\tilde{f}_{PAD}$	Parity Equation	[117]	Least square residual evaluation with sliding data window.	Minimizing noise effect and accurate fault size estimation.	Pitch sensor fault effect and pitch bias are not considered.
			[75]	Robust residual filtering.	Considering both pitch sensor and pitch actuator dynamic change.	No sensor noise is considered.
		Observer Design	[108]	H-/H∞ optimization method.	Optimal residual sensor noise attenuation.	
		Observer Design	[84]	Adaptive observer gains.	Sensor noise and sensor faults are considered. Adaptive observer is only sensitive to dynamic change.	Sensitive to design parameters. Complex procedure using computer simulation.
			[32]	Sliding mode observer.	Facilitate the real-time implementation.	No sensor noise is considered.
		Bayesian fault probability	[94]	Evaluation of the SCADA alarm data.	Reduced false alarm and missed fault rates.	Sensor noise and faults are not considered. The low sample rate of SCADA data.
		Neural networks	[95]	A pattern recognition structure.	Robustness against sensor noise and model uncertainty.	No sensor fault is considered.
Pitch Actuator Bias	β_{bias}	Observer Design	[118]	Kalman filter observer.	Good sensor noise attenuation	Pitch actuator uncertainty and dynamic change are not considered.
Electrical Pitch Actuator Time Delay Change	-		[82]	Sliding mode observer fuzzy T-S model.	More accurate wind turbine model. The reduction of modelling	The effective design of fuzzy rules and set-memberships. Sensitive to design parameters.

					uncertainty on the fault detection.	

4.3. Generator and converter fault detection

The Maximum Power Point Tracking (MPPT) of variable speed wind turbines is achieved by regulating the electrical generator torque using converter current control. The generator torque control leads to adjustment of the generator and rotor speeds to the desired values such that consequently, the power coefficient C_p is maintained at the maximum possible one. Accordingly, the generator faults including bias f_{T_g} and dynamic change $\Delta\tilde{f}_{GC}$ cause the deviation of operation from the intended one. So, it is important to detect and isolate the generator faults. The large variety of wind turbine manufacturers inevitably results in different manufacturer-specific wind turbine generator technology [119]. Accordingly, it is fruitful to consider the generator FDI methods in the system control level, for the various different electrical generator topologies, as outlined in this section. The available FDI methods for the generator bias are summarized in Table 7.

In [44], a wind turbine LPV model, including uncertainty, uses a LPV observer designed to generate the residual, and adopting the adaptive threshold method the generator torque bias is detected. In [79] three different generator FDI schemes are considered. In the first scheme two cascade Kalman filters are utilized for mitigation of the nonlinear aerodynamic torque effect. In the second scheme, a bank of dedicated observers is exploited. The third scheme is designed using a $H\infty$ filter with parity equations, by considering the nonlinearity as a bounded disturbance. Also, in [120], by adopting interval observers and considering the noise and modelling errors as bounded unknowns, the generator fault is detected using online analysis of observed fault signatures and comparing them with the theoretical ones obtained using structural analysis. The fault size is estimated based on the batch least squares approach.

The parity relation, using analytical redundancy relations and interval observers, for uncertain wind turbine model, was developed in [27]. On this basis, using the set-membership approach, the generator bias is accurately detected. Similarly, in [100, 121], a consistent set with measurements is generated using the set-membership approach. Model-reality mismatch, noise, and uncertainties on the torque coefficient and generator fault are included in the wind turbine model. An effective wind speed estimator is proposed. For representing the consistent set of models with measurements, a matrix zonotope is used, which results in a computationally efficient scheme. The results confirm the effectiveness of the proposed method compared to other methods for the same fault scenario. The approach does not need to use threshold design, which is an outstanding advantage of the proposed method.

In [14], the fuzzy theory is exploited to manage uncertain models and noisy data. The residual signals, which are only sensitive to generator faults, are generated using fuzzy T-S prototypes. The data-driven diagnosis strategy, based on fuzzy T-S prototypes is proposed in [45] for converter FDI with generator and sensor faults. The reliable regulation of the generator torque, including both generator uncertainties and faults, is studied in [20], and two different schemes are developed. Firstly, a FIS is proposed for parameter adaptation, without any prior knowledge of the generator faults. In the second approach, the fuzzy T-S identification approach was exploited, to develop an integrated FDI scheme to detect potential generator faults using online diagnostic information. The adaptive fault estimation is exploited in [42] for generator and converter FDI. Also, in [29] a two-dimensional polynomial is suggested to estimate the power coefficient in an analytical form. Consequently, the adaptive filter is obtained via the nonlinear geometrical approach to detect the generator faults.

4.4. Drivetrain fault detection

The drivetrain can be subjected to changes in its dynamics modeled as ΔK_{dt} and ΔB_{dt} in (4), which may happen very slowly. It causes undesirable oscillations, which may lead to total breakdown which causes long and costly downtime [17]. So, it is important to detect this fault in time. It should be noted that most of the developed FDI methods applied to the drivetrain are considered as signal-based approaches [95], where significant literature reviews can be found in [4, 21-24, 65]. Accordingly, this section considers only the model-based FDI methods. In [75] the parity relation is designed on the drivetrain to generate the residual signal and, via robust filtering the residual signal is evaluated to detect changes in drivetrain dynamics. Also, the wind speed is used in the structure of parity relation assuming that the wind speed estimation is separately available, and it is not affected by the fault occurrence which is generally not true. On the other hand, the measurement noise is not considered. Accordingly, in [81] the Kalman filter is utilized to minimize the noise effect and detect the drivetrain efficiency loss due to wear and increased gear friction. The dynamic change may be considered as the change in the resonance frequency and damping ratio of the drivetrain. In this regard, in [41], this change is detected by designing a filter and using only the generator speed measurement. The uncertainties of the drivetrain dynamic response, i.e. unknown aerodynamic torque T_a in (4), and high sensor noise, have led to the development of more advanced FDI solutions. In [96], a neural network was designed for drivetrain FDI by training the network with a large amount of fault-free data to attenuate uncertainty and noise effects. Also, in [90, 122], utilizing fuzzy T-S prototype modelling, the drivetrain fault was detected by designing a sliding mode observer with adaptive gain. Also, the fault size was identified using an equivalent output injection method.

4.5. Aerodynamic characteristic change detection

Debris build-up and blade erosion reduces the blade aerodynamic efficiency, as can be seen in (3). As a result, the captured aerodynamic torque and power are decreased. Also, the uneven oscillation of blades is a reported issue of this change [123]. Furthermore, the power regulation by blade pitch angle adjustment is not satisfactorily achieved. So, it is very important to foresee the aerodynamic characteristic change in the controller design and to detect this potential change. This change is difficult to detect because it is challenging to determine if reduced power generation is due to the blade debris/erosion, or if the wind speed has dropped [124]. Also, as debris build-up happens slowly, it is mostly assumed that this change lies within the annual wind turbines maintenance/inspection and the blades are cleaned/replaced. So, the literature focusing on this change is still limited. In [100], the blade aerodynamic change is described as the uncertainty on the torque coefficient. Accordingly, a consistent set of models is generated using measurements and the nominal wind turbine representation, which includes uncertainties and noise, and by means of the set-membership approach. This set includes all possible states consistent with the fault-free system. If the current measurement is not consistent with this set, a fault is detected. Also, it is stated that when the torque coefficient change is introduced, some faults are not detectable. Consequently, in [25, 125] instead of the individual wind turbine FDI, the blade debris build-up and erosion are detected at the wind turbine farm level and it is shown that this change is easier to be detected at this scale. This is achieved by comparing the output powers of the wind turbines operating under almost the same wind conditions. The nonlinear wind turbine model is obtained by fuzzy T-S modelling. Also, the FDI scheme comprises a rule-based threshold test logic for residual evaluation.

Table 7. Generator bias FDI methods.

Fault Detection Method	Reference	Characteristic	Advantage	Disadvantage
LPV observer based residual generation	[44]	LPV model of wind turbine including uncertainty and adopting the adaptive threshold.	Missed/false alarms are reduced.	Sensitive to design parameters. Complex procedure on Simulation.
Cascade Kalman filters/ observers bank/ $H\infty$ filtering using parity equations	[79]	Three different detection schemes are compared.	Nonlinearity is considered, and bounded uncertainty is attenuated.	Generator sensor fault is not considered in the proposed scheme.
Interval observers design.	[120]	Observed fault signatures are matched with theoretical ones using structural analysis. Fault size estimation using batch least squares.	Unknown and bounded noise and modelling errors are considered.	Overly simplified modelling assumptions in the design which makes it less practical.
Set-membership approach	[27]	Analytical redundancy relations and interval observers.	Unknown and bounded uncertain wind turbine nonlinear model is considered	Complex procedure for implementation.
	[100, 121]	Model of the wind turbine including uncertainties, noise, uncertainties on the torque coefficient and generator fault.	Effective wind speed estimator is proposed. Matrix zonotope is used to reduce computational complexity. No need for threshold design	The generator sensor noise is not considered.
Fuzzy T-S residual generation	[14]	Approximating uncertain nonlinear wind turbine models with fuzzy theory.	Managing noisy data. Residual is sensitive only to generator faults.	The effective design of fuzzy rules and set-memberships. Sensitive to design parameters.
	[45]		Detection and isolation of both generator/converter actuator and sensor faults.	
Fuzzy inference mechanism/ fuzzy T-S identification	[20]	Parameter adaptation without any knowledge of generator faults. Integrated fault detection.	Considering both uncertainties and faults on the generator.	
Adaptive fault estimation	[29]	Nonlinear geometric approach	A two-dimensional polynomial is suggested to estimate the power coefficient analytically.	The sensor noise is not considered.

5. Fault-tolerant control of wind turbines

FTC schemes are designed to maintain acceptable performance and stability of the wind turbines as close as possible to the fault-free conditions when faults occur, and to reduce the need for unplanned costly maintenance and unwanted shut downs. FTC techniques are divided into two different schemes, i.e. active and passive. The main difference is that active FTC needs the timely and accurate FDI information to be fed into the controller structure. Also, FDI information can be used in subsequent prescheduled maintenance plans. In contrast, in passive FTC, the controller is designed to be robust against a set of presumed faults. The benefit of the passive approach is that the controller is fixed and neither fault detection nor controller update are needed. However, some performance degradation in faulty conditions is tolerated. Stability is not necessarily guaranteed for the faults other than the considered ones [34].

The wind turbine power control objectives are defined based on the wind speed, which should be considered in FTC design. For the wind speed less than a given lower value, i.e. cut-in wind speed $V_{r,cut\text{-}in}$, the available wind power is not economical enough to overcome the operational cost, so the wind turbine is not put into operation. Also, for the wind speed greater than a given upper value, i.e. cut-out wind speed $V_{r,cut\text{-}out}$, the wind turbine is pitched-to-feather or braked to protect it structurally, despite the high available wind power. The region from $V_{r,cut-in}$ to the rated wind speed, i.e. at which wind turbine starts producing its rated power, is called the partial load region. Also, the region from the rated wind speed to $V_{r,cut-out}$ is called the full load region. In the partial load region, it is aimed to capture as much power as possible from the wind by controlling the generator torque, i.e. design of $T_{g,ref}$ in (8) and keeping the pitch angle at its optimal value, at which the $C_p(\beta,\lambda)$ curve is maximized. In the full load region, the aim is to make the wind turbine produce only its rated power, by controlling blade pitch angle, i.e. design of β_{ref} in (6) and fixing the generator torque at its rated value. In both regions it is desirable to minimize mechanical stress and actuator usage [21]. Also, a scheme is needed for bumpless switching between the controllers in the partial load and full load regions, due to possible inconsistency between controller signal magnitude at the switching time. Otherwise, a bump in the control signal may cause oscillations between the two controllers and consequently, make the wind turbine unstable. Finally, it is crucial to mitigate the structural loads in the design of the baseline controller. Indeed, the loads considerably reduce the wind turbine's lifespan. The most harmful loads appear in the full load region, in which drag and thrust loads on the wind turbine's structure are considerable, including the tower fore-aft vibration and the blades flap-wise oscillation. The aerodynamic torque variation leads to considerable torsional vibration of the drivetrain shaft. So, it is very useful to implement a drivetrain/tower stress damper module to dampen torsional/fore-aft vibrations, respectively. For instance, the filtered generator speed and power can be added to the generator torque and the pitch angle, respectively, to filter out the resonant frequency of the drivetrain/tower. Also, the asymmetrical torsional torques can be reduced via the individual blade's pitch control [20]. Note finally that a comprehensive review on the wind turbines baseline controllers design are available in [35, 126] and not reviewed here.

5.1. Passive fault tolerant control methods

In passive FTC design the controller is optimized for the fault-free case and some degraded performance is guaranteed when some presumed faults occur. The problem is formulated in the following form:

$$u(t) = \arg \underset{u\in U}{\mathrm{Opt}} \left(\underset{f\in F, D\in \bar{D}, V_{r,cut\text{-}in}\le V_r \le V_{r,cut\text{-}out}}{H} \right), \tag{19}$$

where, H is the operational objective index, to be optimized, e.g. maximizing the extracted power, minimizing induced structural stress, drivetrain oscillation and actuation effort. So, this optimization problem involves finding the appropriate control $u(t)$ which belongs to the achievable control U. The considered faults f are in the given presumed faults set F and the applied disturbances D is bounded by $\bar{D}$.

In [33, 43, 127], a wind turbine LPV model in the full load region is considered, whilst the controller is designed to be robust against parameter variations, caused by nonlinear aerodynamics and against pitch actuator faults. Also, it is shown that the designed passive FTC has better performance than an industrial PI controller. In [128] a fuzzy-based framework including *if-then* rules, is presented to regulate both pitch angle and generator torque while adding fault tolerance features to the wind turbine in a passive way. Pitch and generator sensor faults, pitch dynamic change and generator torque bias were considered. In [129] a novel adaptive PID-based fault-tolerant controller with a Nussbaum-type function is proposed to be insensitive against unexpected pitch actuator faults, including pitch actuator bias and effectiveness loss.

5.2. Active fault tolerant control methods

Active FTC can be solved via the Virtual Sensor and Actuator (VSA) approach or the Controller Reconfiguration (CR) scheme. In VSA, the fault information identified from the FDI scheme, is fed into a virtual (software) sensor/actuator module, which is placed between the actual sensor/actuator and the baseline controller, to correct signals in the virtual sensor/actuator such that the fault effect is removed. In VSA, the baseline controller is still in operation, which is an interesting industrial aspect because the existing baseline controller needs no modification [87]. For some faults, e.g. system faults in Table 4, the fault effects cannot be accommodated via VSA. Accordingly, in the CR approach the whole/part of the baseline controller is reconfigured to an alternative controller to guarantee stability and satisfactory performance. The CR is obtained by either modification of the current baseline controller parameters, switching a new controller, or using the available hardware/software redundant components [130, 131]. CR approach has less industrial acceptability due to its complex implementation, but it shows promising performance for the severe faults. The VSA and CR fault accommodations are illustrated schematically in Figure 11.

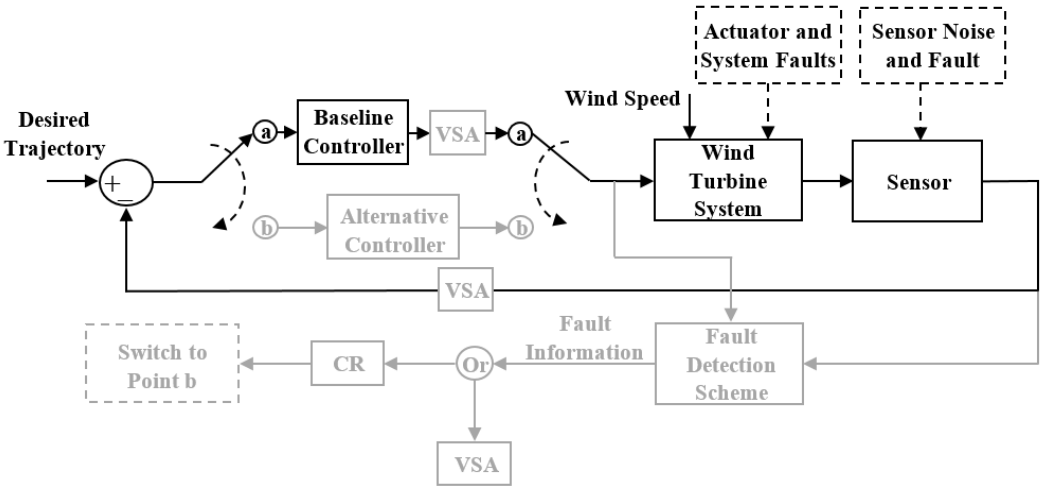

Fig. 11. VSA and CR fault accommodation (grey line) on the wind turbine (black line).

5.2.1. Virtual sensor/actuator faults accommodation

VSA is mostly applied to the wind turbine sensors, because the actuator signal correction may lead to instability, due to inaccurate fault size identification [120]. Also, it is easier to implement the virtual sensor module in practice. In [132] this technique is used to remove the drivetrain sensor faults. Similarly, in [87], VSA is used for pitch and drivetrain sensor faults, including both biased and gained sensor outputs, in which the set-membership approach is used to detect faults. Also, the generator torque bias is accommodated. In [133] using a similar approach, the drivetrain decreased efficiency due to dynamic change is additionally detected and accommodated. Also, in [14], different fault types, including fixed and gained pitch sensor, drivetrain sensors, generator torque offset, drivetrain changed dynamics and pitch actuator dynamic change are considered. In [90], a fuzzy T-S sliding mode observer is designed to estimate and consequently compensate the actuator faults by modifying the controller output via the virtual actuator. In [3] the pitch sensor fault and pitch actuator dynamic change are estimated through the design of an adaptive extended observer for an LPV wind turbine model. The PI industrial controller is used as the baseline controller and its output is corrected with the estimated fault information. Also, the robustness against wind speed variation and model uncertainty is guaranteed by $H\infty$ optimization. In [134], the fuzzy T-S model is used to design an extended state observer, the drivetrain sensor bias is detected and accommodated by correction. The corrected signal is fed into a T-S fuzzy dynamic output feedback controller to maintain the desirable performance. In [29] the proposed scheme exploits a robust actuator fault estimation approach based on adaptive filters. The considered faults are pitch actuator dynamic change, bias and generator torque bias. Accordingly, the output of the PI controller is corrected based on the estimated fault information. Finally, in [25], through the use of expert-generated fuzzy *if-then* rules, the generated power of each wind turbine in the farm is evaluated to detect the possible debris build-up. Accordingly, the generator torque is corrected in the VSA module to compensate for the debris build-up effect and to keep the generated power at the desirable value. It is worth noting that in the VSA the sensor faults are reasonably accommodated better than the system and actuator faults [26].

5.2.2. Controller reconfiguration

Considering the available CR methods, it can be stated that the process and actuator faults are better accommodated [26]. In [135] a group of model predictive controllers are designed to accommodate the pitch actuator dynamic change. A Kalman filter is used to identify the faults, and when detected, an alternative predefined controller is used to compensate for their effects. In [130], modified Ziegler-Nichols rules are applied to the online adaptive controller, relying on the least squares method with adaptive directional forgetting factors, to recursively adjust the PI baseline controller parameters to remove both generator and pitch actuator fault effects. In [136], a FTC scheme is proposed as a combination of model reference adaptive control with neural network compensation. Although, the fault is considered as a bounded additive actuation signal, however, no physically meaningful fault is considered. In [131], a proportional multiple integration observer is designed in the fuzzy T-S framework to estimate the generator sensor faults. Also, a robust estimation of effective wind speed is given. These estimations are used to compensate for the fault effects using a fuzzy T-S dynamic output feedback controller. In [112, 122], by deploying a robust fuzzy scheduler and multi fuzzy observers, a nonlinear wind turbine controller is designed to attenuate the sensor faults, actuator faults and parameter uncertainties on the overall performance. It is desirable to reconstruct and compensate several actuator faults with one observer. In this regard, the sliding mode controller design technique is advantageous.

An adaptive sliding mode observer is designed in [32] to estimate the pitch actuator dynamic change and to modify the traditional PI baseline controller for fault effect compensation. In [34] by combining a disturbance compensator with a controller in the discrete-time domain, pitch actuator FTC is developed. Fault estimation and discrete-time controller designs are simultaneously fulfilled using the disturbance compensator. In [127], the additional redundant pitch, rotor and generator sensors are considered in the proposed controller, to be deployed when fixed/no corresponding sensor outputs are detected. Recently, adaptive control has been used to deal with the faults, as a category of the active/passive combination method. Although, it may be dangerous practically, since this method may mistakenly accommodate faults, for example in critical fault situations, which requires a safety stop of the wind turbine. Accordingly, if the adaptation laws are designed accurately using expert's knowledge, the need for CR is removed to have a simple practical controller similar to passive FTC, and meanwhile, the FDI information is obtained which can be used to improve the maintenance schedules. On the other hand, no presumed fixed fault sets are needed, similar to active FTC. In [31, 92] adaptive laws are defined as a part of the proposed controller to be used in the controller structure and to compensate for the actuator fault effects. In [31] the actuator fault is considered as an additive bounded disturbance, while in [92], pitch actuator dynamic change, pitch bias and generator torque bias are considered. To this end, in Table 8 the available FTC techniques are summarized.

6. Discussion and Future studies

Wind turbine FDI and FTC have recently emerged to support reliable wind power generation. Different FDI schemes are available, which can rely on the accurate modelling, among which fuzzy T-S and LPV are common descriptions. However, it is always desirable to design FDI schemes for the nonlinear model. Effective fault detection is the main step in the active FTC, so it should be well matured before practical implementation. This literature survey highlighted that the focus was on the FDI of the drivetrain and the pitch angle sensors, as these measurements are used in the feedback control system. Table 5 shows that observer design techniques are often used for sensor FDI. The diagnosis of pitch actuator and generator faults require FDI techniques outlined in Tables 6 and 7, respectively, which show that fault observers remain the best solution. Model-based FDI methods applied to the drivetrain are still limited since signal-based methodologies are mostly exploited. The blade aerodynamic change due to debris build-up and erosion can be detected more accurately at the farm level, compared to the individual wind turbine scale.

Table 8. Wind turbine FTC techniques.

			Fault Tolerant Control Method		
			Passive	Active	
				VSA Approach	CR Approach
Fault Source	Sensors	Pitch sensors	Fuzzy T-S multimodel and fuzzy if-then rule-based controller [128].	Set-membership approach [87]. Residual signal generated via fuzzy T-S model [111]. Fuzzy T-S residual generation [14]. Adaptive extended state observer [3].	Robust fuzzy scheduler [112]. Multi-observer switching control [122].
		Drivetrain sensors	-	UIO design [132]. Set-membership approach [87]. Residual signal generated via fuzzy T-S model [111]. Fuzzy T-S residual generation [14]. Fuzzy T-S extended state observer [134].	Multi-observer switching control [122]. Fuzzy T-S Dynamic Output Feedback Controller [131].
		Generator/ Convertor sensors	Fuzzy T-S multimodel and fuzzy if-then rule-based controller [128].	-	-
	Pitch actuator		LPV wind turbine model, robust LMI-based controller [33, 43]. Fuzzy T-S multimodel and fuzzy if-then rule-based controller [128]. Adaptive PID-based controller with Nussbaum-type function [129].	Fuzzy T-S residual generation [14]. Fuzzy T-S sliding mode observer [90]. Adaptive extended state observer [3]. Robust adaptive fault estimation [29].	Model predictive controllers and Kalman filters are used to identify the faults [135]. Ziegler- Nichols rules are applied to adjust the PI controller parameters [130]. Robust fuzzy scheduler [112]. adaptive sliding mode observer to modify traditional PI baseline controller [32]. Fault estimation via adaptive laws within the nonlinear controller [31, 92].
	Drivetrain		-	Set-membership approach [133]. Fuzzy T-S residual generation [14].	-
	Generator and Converter		Fuzzy T-S multimodel and fuzzy if-then rule-based controller [128].	Set-membership approach [87]. Fuzzy T-S residual generation [14]. Fuzzy T-S sliding mode observer [90]. Robust adaptive fault estimation [29].	Ziegler- Nichols rules are applied to adjust the PI controller parameters [130]. Fault estimation via adaptive laws within the nonlinear controller [31, 92].
	Aerodynamic characteristic change		-	Fuzzy if-then rules at farm level [25].	-

The adoption of hardware redundancy is still an effective approach for FDI purposes. On the other hand, the observer design techniques are significant alternatives. Kalman, H∞, UIO, fuzzy T-S, extended LPV and sliding mode observers are the main tools, in which the wind estimation is generally needed, especially for drivetrain sensor FDI. The use of both Kalman and H∞ methods are robustly optimized to minimize the sensor noise effect on the constructed residual. These methods are usually designed on a linearized model and a threshold logic is required. Moreover, the fault isolation task is achieved via fault signature consideration and observer bank design. Regarding the need for wind speed estimation, the UIO design represents a suitable technique to achieve robust estimation. The wind turbine states and faults can be estimated simultaneously by using the extended LPV observer with adaptive observer gain. However, this method is very sensitive to the model accuracy as well as its design parameters. On the other hand, the fuzzy T-S observer can capture the nonlinear behavior of wind turbines. So, the modelling uncertainty effect on the observer performance is reduced. However, the expert's knowledge is needed to be employed to define the proper fuzzy rules. Finally, the sliding mode observer is applied to the nonlinear model, which represents a viable solution for practical implementation. However, it is very sensitive to measurement noise and design parameters. The missed/false fault detection rate is reduced by adopting the set-membership approach in which the threshold need is removed. Nevertheless, an appropriate computational algorithm is needed. Also, the Bayesian framework can be utilized to estimate the fault probability, using SCADA data. However, the sample rate of the signals from SCADA is much too low for general FDI purposes. Neural networks and fuzzy systems are very appropriate for FDI design due to their robustness against sensor noise, model uncertainties and wind speed variation. However, the training stage requires a large amount of fault-free data.

For the fault tolerance feature, the VSA approach is more commonly adopted to compensate for the wind turbine sensor faults. This approach has attracted most of the industrial interest due to its simple implementation. The CR strategy has been considered for accommodating the wind turbine actuator faults. However, accurate fault information is needed. In contrast to active FTC, the passive solutions are designed in a conservative manner, to remove the need for fault detection, and meanwhile to keep the wind turbine working in faulty situations with an accepted performance level, only in specific considered fault situations.

The mitigation of structural loads is a vital step in the control design before installation as an industrial wind turbine controller. The main structural loads are blade root bending moments, tower/nacelle bending moments/acceleration and drivetrain torsion moments [22]. However, most of the designed FTC schemes have been focused on the power control and satisfying operational objectives [1]. For example, in [68, 137] the blade root moment sensor FDI scheme is proposed, using Kalman filtering, for the accurate individual pitch control, which, in turn, reduces the blade fatigue loads. Also, with proper pitch angle regulation, the aerodynamic thrust force can be controlled to reduce the applied bending moment on the blades [27]. In [20, 111], the fuzzy gained scheduled PI controllers are proposed to remove the actuator and sensor faults, respectively, while tower-top fore–aft and side-to-side accelerations, deflections, and moments are investigated and kept at the baseline controller level, which in turn leads to an industrial acceptable controller. Another promising load mitigation FTC approach is wind farm control to reduce the load on a faulty turbine with satisfactory overall demanded power generation [124]. In this regard, in [25], using the proportional distribution algorithm, this objective is met by generator torque correction via FIS, to avoid overloading the remaining healthy turbines and intense control command. It is shown that the proposed FTC scheme has minimal impact on the structural loads during fault accommodation. Finally, to lessen the drivetrain torsion, the generator speed can be band-filtered prior to feeding this signal to the controller, to remove the drivetrain resonant frequency, and consequently, smooth the drivetrain torsion rate [1]. Also, in [92, 129], the proposed FTC schemes are designed on the reduced drivetrain torsion trajectory, to guarantee that the drivetrain torsion is kept at the baseline controller level.

Finally, by considering the issues above, future trends on wind turbines FDI and FTC are suggested in the following.

- Expert's knowledge can be included in the design phase, using soft computing approaches, e.g. fuzzy if-then rules, neural networks or Bayesian frameworks.
- High-fidelity simulators are required for both wind turbine and wind farm systems.
- More realistic fault scenarios need to be implemented and analyzed.
- Accurate performance analysis, verification and validation tools applied to the developed FDI and FTC strategies are required.
- The practical implementation of the designed schemes needs to be assessed in experimental-scale wind turbines and industrial applications.
- Most of the studies have been focused on FDI, rather than FTC design. Moreover, the proposed solutions are mostly developed for a given operational region of the wind turbine. Accordingly, the focus should be on FTC systems, since the FDI task is a by-product. Moreover, the requirements of Industry 4.0 lead to consider adaptive and real-time methodologies, working for the whole operational region of the wind turbine.

- Some faults are better dealt with at the wind farm control level, e.g. blade debris build-up, erosion and slowly developing faults, but the literature is still scarce. So, new schemes for detection, isolation and accommodation of faults at the wind farm level should be investigated.
- Some faults, such as the ones affecting the drivetrain, are detected only via signal-based approaches (e.g. vibration or frequency analysis tools); active schemes should be analyzed for this wind turbine component.

7. Conclusions

In this paper, the most common model-based FDI and FTC techniques for wind turbines and wind farms were outlined and reviewed, motivated by the need for more reliable wind power generation and lower operational cost. Indeed, these techniques can improve the wind turbine operation not only in fault-free conditions, but also in faulty situations. This review paper was prepared in a tutorial fashion to be suitably used for further studies. Firstly, different wind turbine modelling tools including all possible fault situations are considered. Different FDI methods applied to wind turbines were introduced and their applications to the most common fault cases were also discussed. FTC methods were also outlined as a second step to achieve proper fault tolerance features. Finally, future trends were suggested to drive further researchers' studies, which represent viable and effective solutions for industrial applications.

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