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Wind Turbine Power Maximisation Based On Adaptive Sensor Fault Tolerant Sliding Mode Control

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Abstract— **This paper presents a new strategy to robust fault tolerant control (FTC) to optimise the wind energy captured by a wind turbine operating at low wind speeds, using an adaptive gain Sliding Mode Control (SMC). In addition to the inherent robustness of SMC against matched model uncertainty, the proposed method involves a robust descriptor observer design that can provide robust simultaneous estimation of states and the "unknown outputs" (sensor faults and noise) in order to guarantee the robustness of the sliding surface against unknown output effects. Moreover, the sliding surface is designed to achieve the required objectives by utilizing the nonlinear flexible two mass model of the variable speed wind turbine. The proposed FTC SMC method is applied to a 5 MW wind turbine benchmark model.**

I. Introduction

Owing to incessant cost augmentation, unpleasant ecological impact, and restricted reserves of fossil fuel on one hand, and the technological progression, governmental support, and reliance on effortless and renewable energy resources on the other hand, the subject of renewable energy continues to attract significant attention in the literature [1]. Although wind energy is one of the foremost types of renewable energy, in recent years various concerns about the suitability of wind power technologies for efficient and reliable electricity generation have increased significantly [2]. Increase in the share of wind power in relation to the total power generation is closely related to reducing the expenditure per generated kilowatt and the enhancement of the quality of generated power. To cope with this cost challenge, the sizes of wind turbines have become larger; the increase in turbine size implies more power output since the energy captured is a function of the square of the rotor radius. Therefore, larger wind turbines often result in compact expenditures since their production, installation and maintenance costs are lower than the sum total of the outputs of smaller wind turbines attaining the same output power. Furthermore, the fact that offshore wind speed is appreciably *higher* the wind speed, results in enormous motivation to launch offshore wind projects [2].

Although there is a growing deployment of horizontal axis wind turbines there is a poor realization in the industry of the degree to which the control can be used to maximize the wind power available from the wind. The essential problem is to overcome adaptively the non-linear nature of the wind energy. The wind represents an uncontrollable and stochastic source of energy which is proportional to the cube power of the effective wind speed acting in the rotor. Hence, advanced control systems are required to optimise wind turbine operation as well as mitigate the effects of induced loads [3, 4].

In the literature, recent published studies have focused on the development of multi-objective control strategies that can cope with inherent system restriction whilst optimising wind power harvesting [5-7]. Moreover, to reduce maintenance costs and handle the situations in which some wind turbine parts are affected by faults, FTC and fault detection and diagnosis systems have been recognized as the proper solution of retaining acceptable performance as well as to prevent subsystem faults from turning into failures [8-11].

This paper presents a new approach to robust FTC for wind turbines based on the use of an adaptive gain SMC. This adaptive system provides wind turbine power maximization, valid for low wind speed operation. The strategy involves the design of a robust descriptor observer to afford an estimation of the unmeasurable feedback signal together with simultaneous estimation of the "unknown outputs" in order to guarantee robustness of the overall control strategy against sensor faults and noise.

The paper is organized as follows: Section II outlines a flexible two-mass wind turbine model used in the study. Section III presents a suitable control strategy for this dynamical system. In Section IV simulation results are presented showing the application of the proposed control strategy to a 5 MW wind turbine benchmark model [9]. Finally, a set of conclusions are listed in Section V.

II. Wind turbine modelling

A wind turbine model is obtained by combining the constituent subsystem models that together make up the overall wind turbine dynamics. This Section presents the combination of a flexible low speed shaft model together with a two-mass conceptual model of a wind turbine.

The aerodynamic torque (T_a) acting within the rotor represents the principal source of nonlinearity of the wind turbine. T_a depends on the rotor speed ω_r , the blade pitch angle β and the *effective aerodynamic wind speed* v. The aerodynamic power captured by the rotor is given by:

$$P_{cap} = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\beta)v^3 \quad (1)$$

where ρ is the air density, R is the rotor radius, and C_p is the power coefficient that depends on the blade pitch angle (β) and the tip-speed-ratio (λ) (TSR) defined as:

$$\lambda = \frac{\omega_r R}{v} \quad (2)$$

The non-linear aerodynamic torque is thus:

$$T_a = \frac{1}{2}\rho\pi R^3 C_q(\lambda,\beta)v^2 \quad (3)$$

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where $C_q = \frac{C_p}{\lambda}$ is the torque coefficient.

The drive train is responsible for gearing up the rotor rotational speed to a higher generator rotational speed. The drive train model includes low and high speed shafts linked together by a gearbox modelled as a gear ratio. The state space model of the wind turbine drive train has the form:

$$\begin{bmatrix} \dot{\omega}_r \\ \dot{\omega}_g \\ \dot{\theta}_\Delta \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \omega_r \\ \omega_g \\ \theta_\Delta \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} T_a \\ T_g \end{bmatrix} \quad (4)$$

where:

$a_{11} = -\frac{(B_{dt}+B_r)}{J_r}$ $\quad a_{12} = \frac{B_{dt}}{n_g J_r}$ $\quad a_{13} = -\frac{K_{dt}}{J_r}$

$a_{21} = \frac{B_{dt}}{n_g J_g}$ $\quad a_{22} = -\frac{(B_{dt}+n_g B_g)}{n_g^2 J_g}$ $\quad a_{21} = \frac{K_{dt}}{n_g J_g}$

$a_{31} = 1$ $\quad a_{32} = -\frac{1}{n_g}$ $\quad a_{33} = 0$

$b_{11} = \frac{1}{J_r}$ $\quad b_{22} = -\frac{1}{J_g}$

where J_r is the rotor inertia, B_r is the rotor external damping, J_g is the generator inertia, ω_g and T_g are the generator speed and torque, B_g is the generator external damping, n_g is the gearbox ratio, K_{dt} is the torsion stiffness, B_{dt} is the torsion damping coefficient, and θ_Δ is the torsion angle.

Remark 1: The blade pitch subsystem model is not considered here as the pitch angle is held at the optimal setting $\beta = 0$ over the low wind speed range to achieve maximum power extraction (see Fig.1). Furthermore, the converter and generator subsystem is not considered as the proposed controller presented here is designed as an outer controller to provide the inner generator control with the reference torque command. This approach to controller design separation is acceptable since the converter-generator subsystem is faster than the aerodynamic subsystem.

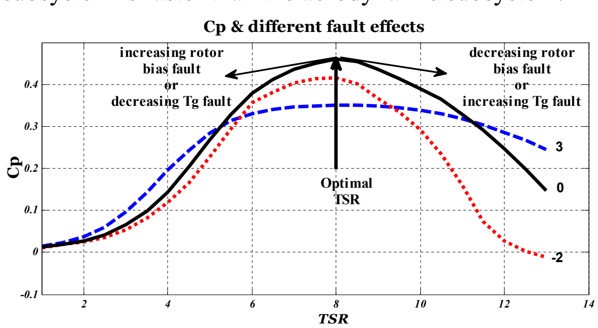

Figure. 1 Power coefficient C_p, TSR, and $\beta = [-2, 0, 3]$

III. Wind Turbine Control and Investigation of Fault Effects

A. Wind turbine control

Generally, wind turbine control objectives are functions of wind speed. For low wind speeds, the objective is to optimise wind power capture through the tracking of optimal rotor speed signals. Once the wind speed increases above its nominal value the control objective moves to the rated regulating power [4, 12, 13].

Specifically, in the low wind speed range of operation, the controller optimises power capture through controlling the generator torque so that the wind turbine rotor speed follows the optimal rotor speed given by:

$$\omega_{ropt} = \frac{\lambda_{opt} v}{R} \quad (5)$$

where ω_{ropt} and λ_{opt} are the optimal rotor speed and the optimal TSR (See Fig. (1)). In fact, from a control point of view, the power optimization problem is a tracking control problem. However, several design constraints must be taken into account in the design of the wind turbine power maximization controller, these are:

1) Wind turbines are characterised by non-linear aerodynamics and have a stochastic and uncontrollable driving force as input in the form of wind speed. This limits the ability of linear control strategies to maintain acceptable performance over a wide range of wind speed.

2) Owing to the direct effect of wind turbine components faults on the wind power conversion efficiency, the controller design must be capable of tolerating different expected fault effects.

3) Exact tracking leads to increased loading on the two drive train shafts and hence can shorten the drive train life time. It is thus very clear that the multi-objective approach cannot be avoided for robust wind turbine control design.

B. Investigation of faults effects

Different fault scenarios are considered in this paper and the proposed control strategy needs to tolerate their effects in the low range of wind speed so that good tracking performance to ω_{ropt} be achieved.

1) *Rotor speed sensor bias fault:* the sensor bias faults (decreasing or increasing) drive the turbine away from its optimal operation. It is very clear that the controller designed to provides good tracking to ω_{ropt} (i.e. $e_t = \omega_{r-measured} - \omega_{opt} \approx 0$). However, due to the scale factor fault the controller now tries to force the faulty measurement to follow ω_{ropt} (i.e. $(1.1\ or\ 0.9) * \omega_r - \omega_{opt} \approx 0$ causing a decrease or increase of the actual rotor speed and hence causing the wind turbine to operate away from the optimal value ω_{opt}.

2) *Fixed rotor speed sensor fault:* the effect of this fault scenario differs based on the fixed measured rotor speed and the ω_{ropt} which in turn depends on the wind speed. If ω_{ropt} is lower than the fixed rotor speed measurement then the controller will force the system to slow down which may lead to rotor stall. On the other hand, if ω_{ropt} is higher than the fixed rotor speed then the controller will simply release the turbine to rotate according to the available wind speed without control.

3) *Generator speed sensor bias fault:* the sensor bias fault (decreasing or increasing) affects the closed-loop performance of the wind turbine and hence the wind power conversion efficiency. However, the expected effect of this fault is probably less than the effect of the rotor speed sensor fault since the generator speed signal is part of the system feedback and does not compare directly with the reference optimal speed.

4) *Generator torque bias fault:* the effect of a torque bias fault is similar to the effect of a rotor speed sensor fault. In this fault scenario the inner generator controller minimises the difference between T_g and the measured generator

torque T_{gm}. In fact, T_{gm} is not directly measured but obtained using a "soft" sensor by robust estimation. Therefore, any bias in this measurement results in driving the system away from optimal operation and hence decreases the wind turbine power conversion efficiency. The effects of different fault scenarios are shown in Fig. (1).

IV. ROBUST FTC BASED SMC

To cope with the wind turbine control requirements listed in Section III, an adaptive SMC methodology for power maximisation of a variable speed HAWT system operating in the low wind speed range. The proposed strategy is shown in Fig. (2).

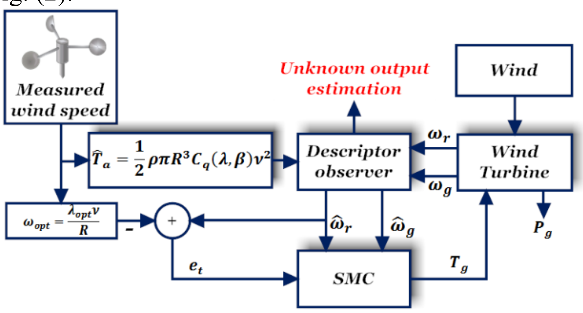

Figure 2 The proposed control strategy

A. Observer design

The control strategy depends on the measurements of rotor and generator rotational speeds (see Fig.2). Indeed, *two* restrictions inspire us to include the observer in the proposed control strategy. Firstly, the rotor rotational speed is heavily influenced by noise and some control strategies shun the use of this signal by considering a good approximation to the rotor speed as given by the generator speed divided by the drive train gearbox ratio, i.e. $\omega_r \approx \omega_g/n_g$. Secondly, the observer can help to tolerate the effects of measurement faults. Therefore, an observer capable of affording simultaneous states and unknown output estimation is necessary. In this subsection, the design of a linear *descriptor observer* that simulates the design methodology in [14] is proposed to provide simultaneous state and *unknown output* estimation.

Remark 3: Due to the presence of an "unknown input" signal in the form of the aerodynamic torque, the proposed observer is fed with the approximate estimation of the unknown aerodynamic signal computed using Eq.(3) and the hub measured wind speed. However, the observer design considers the robustness against the estimated uncertain aerodynamic torque signal by minimizing the $\mathcal{L}_2$ norm of the aerodynamic torque estimation error against state and noise/fault estimation error.

Let Eq.(4) be re-written as:

$$\left.\begin{aligned} \dot{x} &= Ax + B_1 T_a + B_2 T_g \\ y &= Cx + \xi \end{aligned}\right\} \qquad (6)$$

where $x \in \mathcal{R}^n$ is the state vector, $y \in \mathcal{R}^p$ are the outputs (measured states), and $\xi \in \mathcal{R}^p$ are the unknown outputs. From (6), the augmented descriptor system can be defined as:

$$\left.\begin{aligned} \bar{E}\dot{\bar{x}} &= \bar{A}\bar{x} + \bar{B}_1 T_a + \bar{B}_2 T_g + \bar{N}\xi \\ y &= \bar{C}\bar{x} \end{aligned}\right\} \qquad (7)$$

where:

$$\bar{E} = \begin{bmatrix} I_n & 0 \\ 0 & 0 \end{bmatrix} \quad \bar{A} = \begin{bmatrix} A & 0 \\ 0 & -I_p \end{bmatrix} \quad \bar{B}_1 = \begin{bmatrix} B_1 \\ 0 \end{bmatrix}$$

$$\bar{B}_2 = \begin{bmatrix} B_2 \\ 0 \end{bmatrix} \quad \bar{N} = \begin{bmatrix} 0 \\ I_p \end{bmatrix} \quad \bar{x} = \begin{bmatrix} x \\ \xi \end{bmatrix}$$

$$C_o = \begin{bmatrix} C & 0 \end{bmatrix} \quad \bar{C} = \begin{bmatrix} C & I_p \end{bmatrix}$$

The proposed linear descriptor observer dynamics are:

$$E_o\dot{z} = A_o\bar{x} + \bar{B}_1\hat{T}_a + \bar{B}_2 T_g \qquad (8)$$

$$\hat{x} = z + K_o y \qquad (9)$$

where $z \in \mathcal{R}^{n+p}$, $\hat{x} \in \mathcal{R}^{n+p}$, and $\hat{T}_a$ are the auxiliary state vector, the augmented state estimate, and the aerodynamic torque estimation and $E_o, A_o \in \mathcal{R}^{(n+p)*(n+p)}$, and $K_o \in \mathcal{R}^{(n+p)*p}$ are the design matrices. Substituting Eq.(9) into Eq.(8) and subtracting the result from Eq.(7) yields:

$$\begin{aligned} (\bar{E} + E_o K_o \bar{C})\dot{\bar{x}} - E_o\dot{\hat{x}} &= (\bar{A} + A_o K_o C_o)\bar{x} - A_o\hat{x} + \bar{N}\xi \\ &\quad + A_o K_o \xi + \bar{B}_1 e_{T_a} \end{aligned} \qquad (10)$$

where $e_{T_a} = T_a - \hat{T}_a$.

Let $\bar{e} = \bar{x} - \hat{x}$. If the following equalities are hold:

$$\bar{A} + A_o K_o C_o = A_o \qquad (11)$$

$$\bar{N} = -A_o K_o \qquad (12)$$

$$\bar{E} + E_o K_o \bar{C} = E_o \qquad (13)$$

Then the estimation error dynamics are determined by:

$$E_o\dot{\bar{e}} = A_o\bar{e} + \bar{B}_1 e_{T_a} \qquad (14)$$

Using Eqs. (11-13) the design matrices can be determined as:

$$A_o = \begin{bmatrix} A & 0 \\ -C & -I_p \end{bmatrix} \qquad (15)$$

$$K_o = \begin{bmatrix} 0 \\ I_p \end{bmatrix} \qquad (16)$$

$$E_o = \begin{bmatrix} I_n + RC & R \\ MC & M \end{bmatrix} \qquad (17)$$

Then the error dynamics of Eq.(13) become:

$$\begin{aligned} \dot{\bar{e}} &= \begin{bmatrix} I_n + RC & R \\ MC & M \end{bmatrix}^{-1} \begin{bmatrix} A & 0 \\ -C & -I_p \end{bmatrix} \bar{e} + \begin{bmatrix} I_n + RC & R \\ MC & M \end{bmatrix}^{-1} \begin{bmatrix} B_1 \\ 0 \end{bmatrix} e_{T_a} \\ &= \begin{bmatrix} A + RM^{-1}C & RM^{-1} \\ -CA - (M^{-1} + CRM^{-1})C & -(M^{-1} + CRM^{-1}) \end{bmatrix} \bar{e} + \begin{bmatrix} B_1 \\ -CB_1 \end{bmatrix} e_{T_a} \end{aligned} \qquad (18)$$

In order to ensure the stability of the error dynamics and attenuate the effect of e_{T_a} the following inequality must hold:

$$\dot{v}(\bar{e}) + \bar{e}^T\bar{e} - \alpha^2 e_{T_a}^T e_{T_a} < 0 \qquad (19)$$

where $\dot{v}(\bar{e})$ is the derivative of the following Lyapunov function:

$$v(\bar{e}) = \bar{e}^T P \bar{e} \qquad (20)$$

where $P = \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix}$ and $P > 0$. After simple manipulation and making use of the variable changes $q_1 = P_1 R M^{-1}$, and $q_2 = P_2(M^{-1} + CRM^{-1})$ it follows that the observer of Eqs.(7) & (8) is stable and the performance is guaranteed with an attenuation level α, if the following inequality holds true:

$$\begin{bmatrix} \psi_{11} & \psi_{12} & P_1 B_1 \\ * & \psi_{22} & -P_2 C B_1 \\ * & * & -\bar{\alpha} \end{bmatrix} < 0 \quad (21)$$

$$\psi_{11} = P_1 A + (P_1 A)^T + q_1 C + (q_1 C)^T + I_n$$
$$\psi_{12} = q_1 - (P_2 C A)^T - (q_2 C)^T$$
$$\psi_{22} = -(q_2 + q_2{}^T) + I_p$$
$$\alpha = \sqrt{\bar{\alpha}}$$

After solving the LMI of Eq.(21) the design variables M and R can be determined as:

$$M = (P_2^{-1} q_2 - C P_1^{-1} q_1)^{-1} \quad (22)$$
$$R = P_1^{-1} q_1 M \quad (23)$$

Hence, by substituting the computed M and R in Eq.(17) all observer gains are determined.

B. *Controller Design*

SMC is characterised by its invariant property against modelling uncertainty once the system is forced to enter the designed sliding surface. The SMC design steps include construction of the sliding surface that ensure the achievement of control goals, the design of a control signal that forces the system towards the sliding surface, and the design of the discontinuous control signal around the sliding surface to ensure that the system remains in the vicinity of the sliding surface.

It is clear from Fig. 1 that the power coefficient has a unique maximum which corresponding to the optimal power captured. Also the maximum corresponds to a specific optimal value of the TSR (λ_{opt}). Hence, to ensure power maximisation the control strategy must force the wind turbine to operate in the vicinity of this optimal tip-speed-ratio.

The sliding mode surface must be designed such that when the system reaches the sliding mode the control objectives are achieved.

Now define the tracking error as follows:

$$e_t = \omega_r - \omega_{opt} \quad (24)$$

The first and second order differential equation of the tracking error can easily be obtained based on (4) and (24), as:

$$\dot{e}_t = a_{11}\omega_r + a_{12}\omega_g + a_{13}\theta_\Delta + b_{11}T_a - \dot{\omega}_{opt}$$
$$\ddot{e}_t = \ddot{\omega}_r - \ddot{\omega}_{opt} \quad (25)$$

For the second order tracking error dynamics the proposed sliding surface is given by:

$$S = \dot{e}_t + \gamma e_t \quad (26)$$

Remark 4: It is clear that while the system is in the sliding mode ($S = 0$) the unique solution to (26) occurs for $e_t = 0$. Hence, the first objective is achieved. Furthermore, while the system trajectory is in the sliding manifold the dynamics are reduced to a first order differential equation with time response governed by the positive design parameter (γ), selected such that the second objective is achieved.

Remark 5: It should be noted here that the sliding surface is robust against sensor faults and/or noise. This robustness arises from the insertion of the descriptor observer that can estimate and compensate the sensor faults and noise. Hence, $\widehat{\omega}_r$ is used as good (fault and noise-free) approximation to ω_r.

Hence, the most important challenge is to find the control signal that causes the sliding surface to attract the system trajectory to reach and remain in the sliding surface vicinity. The necessary condition is:

$$\dot{S}S \le -\tau|S| \quad (27)$$

In the SMC literature this condition is known as the 'reachability condition'. The second step is to find the '*equivalent control*' required to satisfy this reachability condition.

$$\dot{S} = \ddot{e}_t + \gamma \dot{e}_t \quad (28)$$

$$\dot{S} = a_{11}(a_{11}\omega_r + a_{12}\omega_g + a_{13}\theta_\Delta + b_{11}T_a) + a_{12}(a_{21}\omega_r + a_{22}\omega_g + a_{23}\theta_\Delta + b_{22}T_g) + a_{13}(a_{31}\omega_r + a_{32}\omega_g + a_{33}\theta_\Delta) + b_{11}\dot{T}_a - \ddot{\omega}_{opt} + \gamma\dot{e}_t$$

$$\dot{S} = a_{11}b_{11}T_a + a_{12}b_{22}T_g + \tilde{a}_{11}\omega_r + \tilde{a}_{12}\omega_g + \tilde{a}_{13}\theta_\Delta + b_{11}\dot{T}_a - \ddot{\omega}_{opt} + \gamma\dot{e}_t \quad (29)$$

where:

$$\tilde{a}_{11} = a_{11}a_{11} + a_{12}a_{21} + a_{13}a_{31}$$
$$\tilde{a}_{12} = a_{11}a_{12} + a_{12}a_{22} + a_{13}a_{32}$$
$$\tilde{a}_{13} = a_{11}a_{13} + a_{12}a_{23} + a_{13}a_{33}$$

When the system reaches the sliding vicinity $S = 0 \Rightarrow \dot{S} = 0$, then the equivalent control signal is:

$$T_g = \frac{-1}{b_{22}a_{12}}(b_{11}a_{11}T_a + \tilde{a}_{11}\omega_r + \tilde{a}_{12}\omega_g + \tilde{a}_{13}\theta_\Delta + b_{11}\dot{T}_a - \ddot{\omega}_{opt} + \gamma\dot{e}_t) \quad (30)$$

Remark 6: Eq. (30) represents the actual equivalent control signal required to bring the wind turbine to the sliding surface. However, an estimate of the aerodynamic torque and torsion angle signals are used here.

Based on Remark 6 an adaptive gain is proposed to overcome the expected estimation error generated from the dependence on the estimated rather than actual signals. Moreover, to reduce the number of derivatives required the control signal must eliminate the terms $b_{11}\dot{T}_a$ and $\ddot{\omega}_{opt}$. Using this, the generator reference torque is given by:

$$T_g = \frac{-1}{b_{22}a_{12}}(b_{11}a_{11}\hat{T}_a + \tilde{a}_{11}\widehat{\omega}_r + \tilde{a}_{12}\widehat{\omega}_g + \tilde{a}_{13}\hat{\theta}_\Delta + \gamma\dot{e}_t + (k(t) + \delta) * sgn(S)) \quad (31)$$

where $k(t)$ is the adaptive gain, and δ is a positive constant. The proposed control signal as shown in (31) consists of *two* components, the linear and discontinuous controls.

Substitution of Eq.(31) in Eq.(29) yields:

$$\dot{S} = b_{11}\dot{T}_a - \ddot{\omega}_{opt} + \mathcal{E} - (k(t) + \delta) * sgn(S) \quad (32)$$

where $\mathcal{E}$ represents the total error between the original signals s and their estimates. Suppose that:

$$h(t) = b_{11}\dot{T}_a - \ddot{\omega}_{opt} + \mathcal{E} \quad (33)$$

The upper bound of $h(t)$satisfies:

$$|h(t)| \le H \quad (34)$$

Consider the following Lyapunov function:

$$V(S) = \tfrac{1}{2}SS + \tfrac{1}{2}(k(t) - H)^2 \quad (35)$$

The time derivative is:

$$\dot{V}(S) = \dot{S}S + (k(t) - H)\dot{k}(t) \quad (36)$$

Using (31) and (32), then (36) becomes:

$$\dot{V}(S) \le HS - k|S| - \delta|S| + k(t)\dot{k}(t) - H\dot{k}(t) \quad (37)$$

To ensure the negativity of (37) the adaptive gain is designed to be equal to:

$$\dot{k}(t) = |S| \quad (38)$$

Hence, the derivative of the Lyapunov function always satisfies:

$$\dot{V}(S) < -\delta|S| \quad (39)$$

Hence, the tracking error converges towards zero. The following remarks highlight the required approximation and constraints of the proposed design.

Remark 7: To avoid the chattering accompanied with sliding motion a well-known approximation to the function $sgn(S)$ is given by [15]:

$$sgn(S) = \frac{S}{|S| + \eta} \quad (40)$$

where η is a small positive constant. This will ensure the sliding motion to be in the vicinity of the line ($S = 0$). However, the adaptive gain presented in (38) is continuously increasing as long as S is away from $S = 0$. Therefore, a slight modification to (38) is introduced below:

$$\left.\begin{array}{ll}\dot{k}(t) = |S| & S > \eta \\ \dot{k}(t) = 0 & S \le \eta\end{array}\right\} \quad (41)$$

IV. Simulation Results

The simulation of the proposed SMC design is based on the wind turbine benchmark system described in [9]. The model is implemented with band-limited white measurements noise. The rotor and generator sensor faults are represented by scaling factor errors. The scaling is 1.1 times the real generator and rotor rotational speeds. The expected fault effects cause the reference generator torque to deviate from the torque required to achieve optimal power generation. Table 1 below shows the parameters used in the benchmark simulation.

Table 1: Wind turbine benchmark parameters.

J_r	$55*10^6\ kg.m^2$	J_g	$390\ kg.m^2$
B_r	$7.11\ kg.m^2.s^{-1}$	B_g	$45.6\ kg.m^2.s^{-1}$
B_{dt}	$775.49\ kg.m^2.s^{-1}.r^{-1}$	K_{dt}	$2.7*10^9\ N.m.r^{-1}$
P_n	$4.8*10^6\ W$	ω_n	$162\ r.s^{-1}$
n_g	95	R	$57.5\ m$
ρ	$1.225\ kg.m^{-3}$	H	$87\ m$

Remark 8: The required derivatives are approximated using a filtered derivative approximation of the form $(\frac{s}{T_f s+1})$.

Remark 9: Without loss of generality, the output matrix parametric fault presented in wind turbine benchmark model [9] can be represented as an additive fault in which the fault signal depends on the measured state, as illustrated below:

$$y_f = C_f x = \begin{bmatrix}1 & 0\\ 0 & 0.9\end{bmatrix}\begin{bmatrix}x_1\\ x_2\end{bmatrix} = Cx + \begin{bmatrix}0\\ 1\end{bmatrix}(-0.1 * x_2) \quad (42)$$

Hence, parameter changes in the output matrix C can be considered as a special case of additive faults in which the fault signal (f_s) is a scaled version of the measured state.

In the first fault scenario the generator and rotor speed sensor faults are represented by scaling factor errors. The scaling is 1.1 times the real generator and rotor rotational speeds. The expected fault effects cause the reference generator torque to deviate from the torque required to achieve optimal power generation. Fig. (3) shows the measured, actual and estimated generator and rotor speed signals with scaling fault 1.1. The simulation signals show that the rotor rotational speed is highly affected by noise. However, the proposed descriptor observer effectively decouples and estimates the unknown outputs.

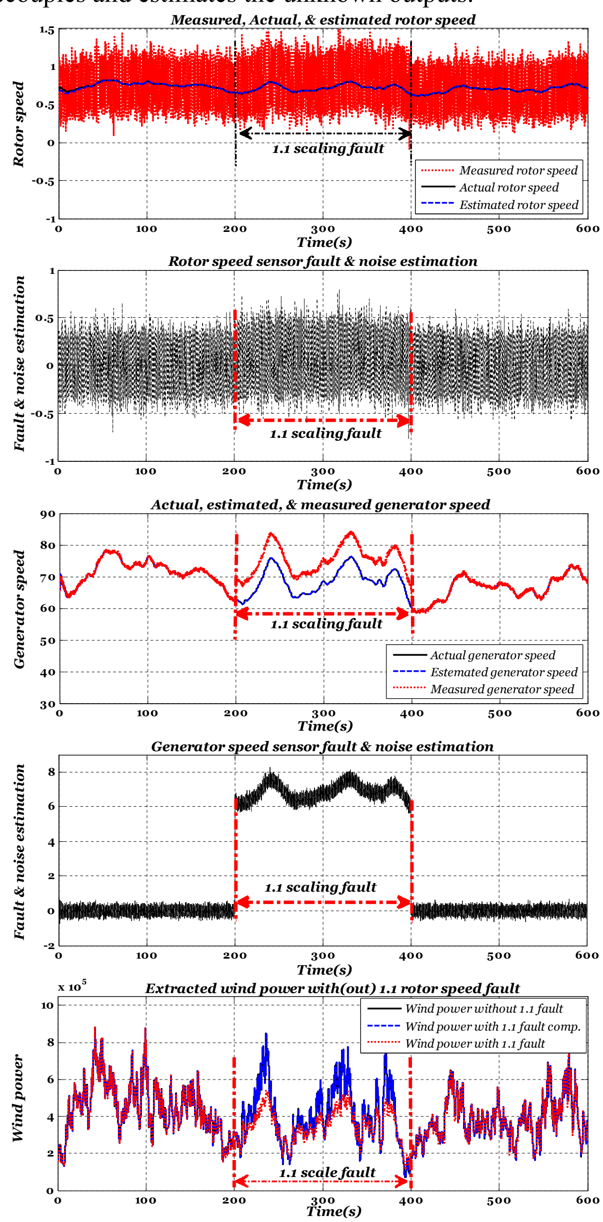

Figure 3: Generator & rotor speed scaling sensor fault & fault estimation

The descriptor observer can also help to produce information about the severity of each fault. This is achieved through taking the ratio between the measured generator speed and

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the estimated signal. Hence, if there are no faults the ratio should be 1 otherwise any deviation from unity indicates the occurence of the fault and the magnitude of the deviation represents the fault severity. Fig. 8 shows the fault evaluation signal for both fault scenarios.

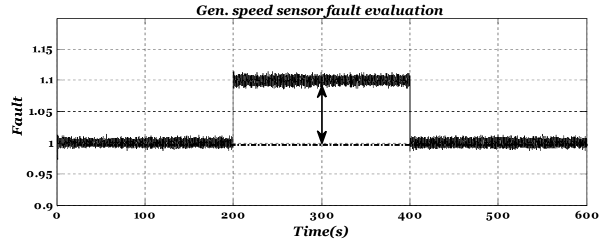

Figure 4**:** Deviation of 1.1 sensor measurement from unity

The second fault scenario is represented by the fixed sensor output of the rotor speed at 1.4 *rpm*. The estimation and compensation of the rotor speed is shown in Fig. (5).

Remark 10: A given measurement is fixed or "stuck" at a constant value g can also be considered as an additive fault as follows:

$$y_f = C_f x = \begin{bmatrix}1 & 0\\ 0 & \frac{g}{x_2}\end{bmatrix}\begin{bmatrix}x_1\\ x_2\end{bmatrix} = Cx + \begin{bmatrix}0\\ 1\end{bmatrix}(g - x_2) \qquad (43)$$

Thus, stuck faults are special cases of additive faults in which the fault signal is a function of the corresponding measured state and the constant g.

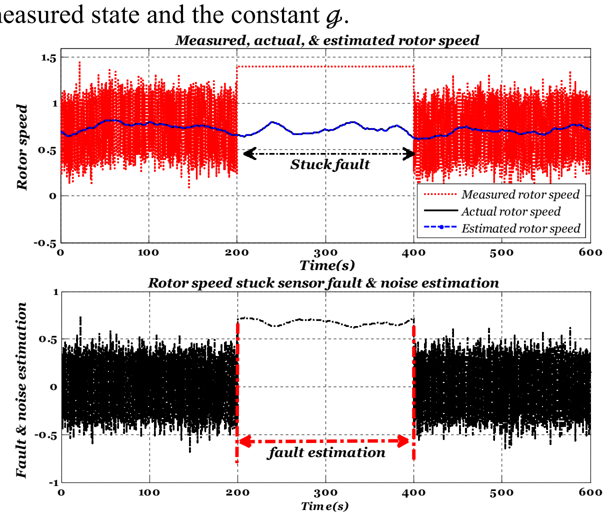

Figure 5. Stuck rotor speed sensor fault

In a similar way to scale fault evaluation, the constant fault evaluation can also be obtained by adding the estimated fault signal with the estimated rotor speed signal since in this fault scenario the fault estimate signal is equal to $(-\omega_r + 1.4)$.

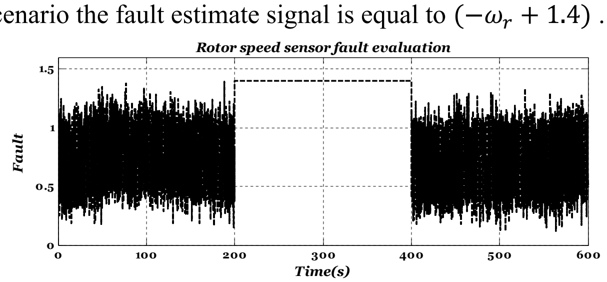

Figure 6. Stuck fault evaluation

V. Conclusion

Wind turbines are complex nonlinear systems that are conceptually driven by an unmeasurable stochastic wind force signal. Sustainability of such systems is highly affected by the chosen control strategy. Hence, the wind turbine control strategy is required to be robust against the effective wind speed variations, modelling uncertainties, and the presence of measurement faults and noise. The control system must also reduce the effects of control action on the system structure and the generated power quality, whilst maintaining acceptable performance. Results are presented illustrating the robustness of an SMC design using the wind turbine benchmark system.

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