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DOI
10.1016/j.ifacol.2023.10.192

Publication date
2023

Document Version
Final published version

Published in
IFAC-PapersOnLine

Citation (APA)
Liu, Y., Brandetti, L., & Mulders, S. P. (2023). Sensor fault-tolerant control for wind turbines: an iterative learning method. *IFAC-PapersOnLine*, *56*(2), 5425-5430. https://doi.org/10.1016/j.ifacol.2023.10.192

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Sensor fault-tolerant control for wind turbines: an iterative learning method

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Abstract: The combined wind speed estimator and tip speed ratio (WSE-TSR) tracking control scheme is widely used to regulate power production for large-scale modern wind turbines. Although very effective, such an advanced control scheme, based on the prior model information, is highly dependent on external measurements. For partial-load region control, the only external information involved is commonly the measured rotor or generator speed. Inaccuracy in such sole measurement results in an unintended turbine operation and might lead to sub-optimal power production and instability. This paper presents a fault-tolerant control (FTC) method, which aims to eliminate the sensor fault effects for modern wind turbine systems. To fulfil this goal, an iterative learning scheme is proposed to detect and estimate the multiplicative sensor fault, on which an adaptive FTC law is formulated such that the effects of the sensor fault are eliminated. Case studies show that the proposed iterative learning FTC method performs well in detecting, estimating, and accommodating the sensor fault under realistic turbulent wind conditions. The advanced wind turbine controller can maintain its control performance even under faulty conditions, preventing further damage to other turbine components and allowing for continuous power production.

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Keywords: Wind turbine, sensor fault, fault-tolerant control, iterative learning scheme, combined wind speed estimator and tip speed ratio tracking control

1. INTRODUCTION

Over the past years, wind energy has played an increasingly vital role in the international energy market. With the 93 GW of new wind installations in 2021, the global wind power capacity was increased to 837 GW (Global Wind Energy Council, 2022). However, to meet the net zero emission target by 2050, a four times annual installation capacity acceleration is needed in 2022 – 2026 (Komusanac et al., 2022). The ambitions mentioned above inevitably demand scaling up the rated power generation. Therefore, to empower wind power's next era of growth, the most cost-effective and economically viable solution for wind energy is to enlarge wind turbine sizes.

With the increasing dimensions and the resulting complexity in structural dynamics, turbines are becoming more susceptible to unexpected events (Carroll et al., 2016). This large-scale vulnerability aspect increases demand for further optimization of wind turbine control systems. The turbine's control strategy is becoming ever more complex, and the correct functioning and reliability of the control system are of utmost importance to prevent turbine damage from system faults and failures.

Modern wind turbines are equipped with an advanced control system consisting of a wind speed estimator and a tip-speed ratio tracking controller. Only limited measurements are required in such a scheme. The only external information needed for partial-load region control is commonly the measured rotor or generator speed. Inaccuracy in this sole measurement inevitably leads to unintended turbine operation, possibly leading to suboptimality in terms of power capture or stability.

A few fault diagnosis and tolerant control methods have been developed to counteract the effects of sensor faults in wind turbine systems over the past years (Odgaard and Johnson, 2013). Some contributions aim at detecting and isolating sensor faults to maintain nominal wind turbine performance. Subspace identification and Kalman filter techniques (Wei et al., 2010) were used to detect and isolate a blade sensor fault. An unknown input observer (Odgaard and Stoustrup, 2010) was designed to accommodate multiple sensor faults. A three-stage method was proposed to detect and isolate sensor faults for wind turbine condition monitoring (Peng et al., 2018).

In contrast to the abovementioned methods, this paper presents a novel iterative learning fault-tolerant control (FTC) method and focuses on inaccuracies in the rotor speed measurement signal resulting from a sensor fault. The proposed FTC method leverages the inherent information and structure in advanced wind turbine controllers. The method consists of steps for fault detection, estimation, and accommodation to mitigate the fault effects in a purely data-driven manner. It relies on the key assumption that the rotor effective wind speed (REWS) is measurable. In industrial practice, the REWS is usually obtained via the hub-height anemometer and/or light detection and ranging (LIDAR) measurement campaign for calibration purposes.

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10.1016/j.ifacol.2023.10.192

The proposed method augments advanced wind turbine controllers with fault-tolerant potential providing resilience against uncertainty and/or inaccuracy in the rotor speed measurement. In more detail, this is substantiated by providing the following contributions:

(1) Exhibiting the potential that by exploiting the information on the REWS and the wind turbine prior model, the sensor fault can be detected, estimated and accommodated in a purely data-driven iterative manner.
(2) Showing that the widely-used wind turbine torque controller, i.e. the combined wind speed estimator and tip speed ratio (WSE-TSR) tracking control scheme, benefits from the proposed learning method for tackling the sensor fault occurring at the rotor speed measurement.
(3) Evaluating the validity of the learning method under realistic turbulent wind conditions and multiplicative sensor fault scenarios.

The remainder of the paper is organized as follows. Section 2 describes the wind turbine model and its partial-load region control scheme considered in this paper. Section 3 details the theoretical framework of the iterative learning FTC method. Next, a case study illustrating the FTC performance under turbulent wind conditions is demonstrated in Section 4. Finally, Section 5 presents concluding remarks.

PREREQUISITES

This section introduces the prerequisites needed for the development of the iterative learning FTC method. Throughout the whole paper, measured and estimated quantities are indicated by $\tilde{(\cdot)}$ and $\hat{(\cdot)}$, respectively. The time derivative is denoted by $\dot{(\cdot)}$.

The following assumptions are imposed on the presented wind turbine model and control scheme.

Assumption 1. *Only the rotor speed measurement is considered uncertain by a multiplication factor. Other measurements are unaffected, and the internal model included in the turbine control scheme perfectly represents the actual wind turbine system.*

Assumption 2. *The wind turbine operates in the partial-load region, under which only the torque controller is active, and the pitch angle is set to its fine value of zero degrees. Therefore, the power coefficient is only a function of the tip-speed ratio.*

Assumption 3. *An accurate rotor-effective wind speed measurement is available during a short-term calibration campaign.*

Assumption 4. *The aerodynamic power is completely converted to the generator power. Hence, the drive-train efficiency is lossless.*

2. WIND TURBINE MODEL AND CONTROL DERIVATION

This section introduces the derivation of the considered wind turbine model and control scheme. Subsequently, the sensor fault considered in this paper is described.

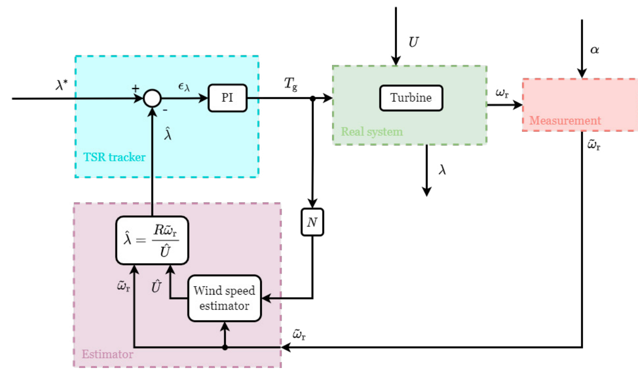

Fig. 1. Block diagram of the combined wind speed estimator and tip-speed ratio tracking control scheme. The green box represents the NREL's 5MW reference wind turbine. The wind speed estimator is indicated in purple, and the tip-speed ratio tracker is indicated in cyan. A sensor fault occurs at the rotor speed measurement in red.

2.1 Wind turbine model and control scheme

In control systems for large-scale modern wind turbines, the REWS estimator is combined with the TSR tracker to achieve dynamic torque (or power) control, such that the rotor is regulated at the desired operating point. The overall structure of the wind turbine model as well as the control scheme is sketched in Fig. 1 and explained below.

First, the wind turbine dynamics are formulated as a first-order system as

$$J\dot{\omega}_g = T_r/N - T_g \,, \tag{1}$$

where J is the equivalent inertia at the generator high-speed shaft (HSS) obtained from $J = J_g + J_r/N^2$, with J_r and J_g being the rotor and generator inertia. The gearbox ratio is defined as $N = \omega_g/\omega_r$, representing the transmission between the generator speed ω_g and the rotor speed ω_r, whereas T_r and T_g are the aerodynamic and generator torque, respectively. The former mentioned is given by

$$T_r := \frac{1}{2\omega_r}\rho A U^3 C_P(\lambda), \tag{2}$$

in which ρ is the air density, A the rotor swept area and U the REWS. The nonlinear power coefficient mapping $C_P(\cdot)$ is a function of the dimensionless tip-speed ratio λ, that is defined as

$$\lambda := \frac{\omega_r R}{U}, \tag{3}$$

in which R is the radius of the rotor.

According to (2), the definition of the turbine's nonlinearity is presented as follows:

$$\Phi(\omega_r, U) := \frac{T_r}{NJ} = \frac{\rho A}{2NJ}\frac{U^3}{\omega_r}C_P(\lambda)\,, \tag{4}$$

and is considered a basis for formulating the REWS estimator. In detail, the extended immersion and invariance (I&I) scheme with a proportional and integral (PI) correction term (Ortega et al., 2013; Liu et al., 2022) is utilized to estimate the REWS, denoted as $\hat{U}$:

$$\begin{cases} \dot{\hat{\omega}}_{\mathrm{r}} = \dfrac{1}{N}\Phi\left(\hat{\omega}_{\mathrm{r}}, \hat{U}\right) - \dfrac{T_{\mathrm{g}}}{NJ} \\ e_{\omega} = \hat{\omega}_{\mathrm{r}} - \tilde{\omega}_{\mathrm{r}} \\ \hat{U} = \gamma e_{\omega} + \beta \displaystyle\int_0^t e_{\omega}(\tau) d\tau \end{cases}, \tag{5}$$

with $\tilde{\omega}_{\mathrm{r}}$ representing the measured rotor speed signals, $\hat{U}$ the estimated wind speed, $\dot{\hat{\omega}}_{\mathrm{r}}$ the partial derivative of the rotor speed with respect to the time, γ the proportional gain, β the integral gain, t the present time, and τ the variable of integration.

Combined with the REWS estimator in (5), the TSR tracker is utilized to operate the wind turbine at the desired set point $\lambda^\star$, providing a generator torque reference with a PI control paradigm

$$T_{\mathrm{g}} = K_{\mathrm{p}} e_{\lambda} + K_{\mathrm{i}} \int_0^t e_{\lambda}(\tau) d\tau \,, \tag{6}$$

in which the error e_{λ} is computed as

$$e_{\lambda} = \lambda^\star - \hat{\lambda} \,, \tag{7}$$

where $\hat{\lambda}$ denotes the TSR estimate, which is computed as

$$\hat{\lambda} = \frac{\hat{\omega}_{\mathrm{r}} R}{\hat{U}} \,. \tag{8}$$

2.2 Sensor fault formalization

This section defines a sensor fault occurring in the measurements of the wind turbine signal. As illustrated in (5) and (6), the performance of the WSE-TSR tracking controller is highly dependent on prior model information and a limited set of measurements.

Under Assumption 1 and according to Odgaard and Johnson (2013), the commonly-investigated multiplicative scaling factor is considered in this paper to model the sensor fault. The multiplicative scaling factor $\alpha : (0, \infty) \to \mathbb{R}_+$ is applied to obtain the measured rotor speed

$$\tilde{\omega}_{\mathrm{r}} = \alpha \omega_{\mathrm{r}} \,, \tag{9}$$

with ω_{r} being the faulty-free actual rotor speed. Under the fault-free condition, α is equal to 1, thus leading to an unbiased measurement. Once the sensor fault occurs, the measurement inaccuracy will lead to a biased estimate of $\hat{U}$ in (5) and thus to a biased $\hat{\lambda}$ in (8). Consequently, the turbine will operate far from the desired optimal condition.

The sensor FTC problem addressed in this paper is formalized as follows.

Problem statement: Consider the wind turbine (1) and the control scheme in (5)–(6) with the unknown measurement uncertainty defined in (9), find a consistent estimate of the scaling factor caused by the sensor fault, such that:

$$\lim_{t\to\infty} \hat{\alpha}(t) = \alpha \,.$$

3. ITERATIVE LEARNING FAULT-TOLERANT CONTROL

In this section, the overall structure of the proposed FTC method is introduced. First, the derivation of the iterative learning method is presented, which is then used to formulate the FTC framework in the subsequent sections.

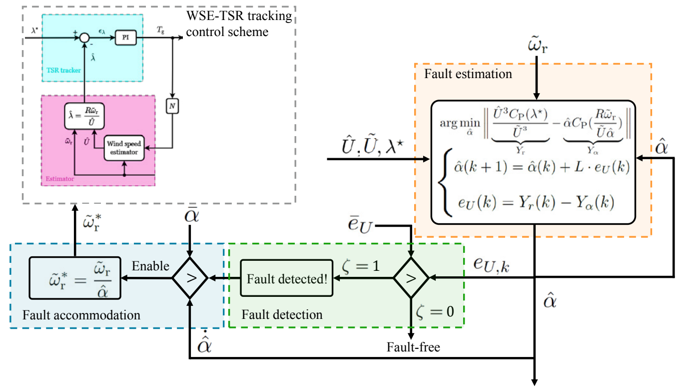

Fig. 2. Block diagram of the iterative learning FTC method.

3.1 Iterative learning method

Under steady-state conditions, and given Assumption 4, the aerodynamic torque in (2) is balanced by the generator torque provided by the WSE-TSR tracking control scheme. Therefore, the following torque balance equation is met

$$T_{\mathrm{r}} = T_{\mathrm{g}} \;\; \Rightarrow \;\; \frac{1}{2}\rho A \frac{U^3}{\omega_{\mathrm{r}}} C_{\mathrm{P}}(\lambda) = \frac{1}{2}\rho A \frac{\hat{U}^3}{\tilde{\omega}_{\mathrm{r}}} C_{\mathrm{P}}(\hat{\lambda}) \,. \tag{10}$$

The estimated TSR is in steady-state enforced to $\lambda^\star$ by the TSR tracker, thus

$$\hat{\lambda} = \frac{R\tilde{\omega}_{\mathrm{r}}}{\hat{U}} = \lambda^\star \,. \tag{11}$$

By crossing out the constant proportion $\rho A/2$, the relation in (10) is rewritten into

$$\frac{U^3}{\omega_{\mathrm{r}}} C_{\mathrm{P}}(\lambda) = \frac{\hat{U}^3}{\tilde{\omega}_{\mathrm{r}}} C_{\mathrm{P}}(\hat{\lambda}) \,. \tag{12}$$

Substituting (9) to (12) respectively, it becomes evident that

$$\alpha U^3 C_{\mathrm{P}}(\lambda) = \hat{U}^3 C_{\mathrm{P}}(\hat{\lambda}) \,. \tag{13}$$

Replacing λ and $\lambda^\star$ with (3) and (11), (14) can be rewritten into

$$\alpha U^3 C_{\mathrm{P}}(\frac{R\omega_{\mathrm{r}}}{U}) = \hat{U}^3 C_{\mathrm{P}}(\lambda^\star) \,. \tag{14}$$

It is worth noting that the real value of the rotor speed ω_{r} is unknown in the real-world scenario due to the unknown multiplicative measurement scaling factor. Therefore, by combining (9) with (14), the following is obtained

$$\alpha U^3 C_{\mathrm{P}}(\frac{R\tilde{\omega}_{\mathrm{r}}}{U\alpha}) = \hat{U}^3 C_{\mathrm{P}}(\lambda^\star) \,. \tag{15}$$

Under Assumption 3, U is replaced with $\tilde{U}$ in (15). Then, moving all the available information to the right-hand side results in

$$\alpha C_{\mathrm{P}}(\frac{R\tilde{\omega}_{\mathrm{r}}}{\tilde{U}\alpha}) = \frac{\hat{U}^3}{\tilde{U}^3} C_{\mathrm{P}}(\lambda^\star) \,. \tag{16}$$

From (16), the scaling factor α induced by the considered sensor fault is the only unknown quantity. It will lead to a biased estimate of TSR, which result in turbine operation away from the desired operating point. The main goal is to obtain a consistent estimate $\hat{\alpha}$ of the unknown quantity α based on all the available information involved.

With the above-derived equations in mind, the optimization problem can be formulated as

$$\arg\min_{\hat{\alpha}} \left\| \underbrace{\frac{\hat{U}^3 C_{\mathrm{P}}(\lambda^\star)}{\tilde{U}^3}}_{Y_{\mathrm{r}}} - \underbrace{\hat{\alpha} C_{\mathrm{P}}(\frac{R\tilde{\omega}_{\mathrm{r}}}{\tilde{U}\hat{\alpha}})}_{Y_\alpha} \right\|, \tag{17}$$

where Y_r includes all the available information for building up the iterative learning method, while Y_α represents those unknown quantities related to α need to be estimated.

Different algorithms can be applied to (17) to estimate $\hat{\alpha}$. In this paper, an iterative learning framework is considered to attain the optimization goal. By minimizing the learning error in the optimization problem the scaling factor can be approximated in an iterative fashion as

$$\hat{\alpha}(k+1) = \hat{\alpha}(k) + L \cdot e_U(k), \tag{18}$$

with L being the learning rate. The learning error $e_U(k)$ at time step k is:

$$e_U(k) = Y_r(k) - Y_\alpha(k). \tag{19}$$

The scaling factor α is successfully estimated if the error e_U is minimized to zero. Based on the aforementioned iterative learning framework, a FTC strategy is presented in the subsequent section, such that the sensor fault can be detected, estimated, and accommodated in an adaptive way.

3.2 Realization of the fault-tolerant control

The block diagram of the iterative learning FTC method has been sketched in Fig. 2. It includes a fault estimation block based on the abovementioned iterative learning method. It is active in monitoring the potential sensor fault of the measured rotor speed signal. An error sample $e_U(k)$ crossing a user-designed threshold $\bar{e}_U$, implies that a sensor fault has been detected at time step k which triggers the fault detection alarm, that is

$$\zeta = \begin{cases} 1\,, \text{if} & |e_U(k)| >= \bar{e}_U \\ 0\,, \text{if} & |e_U(k)| < \bar{e}_U \end{cases}, \tag{20}$$

in which ζ denotes the fault detection alarm signal, and 1 and 0 represent fault and fault-free, respectively. In practice, the threshold $\bar{e}_U$ implies the uncertainties of the learning method induced by the wind turbulence, internal models, etc. It can be determined based on the learning error under the fault-free condition.

Once the sensor is detected, the following condition is given to check if a consistent estimate $\hat{\alpha}$ has been obtained:

$$\dot{\hat{\alpha}} < \bar{\alpha}, \tag{21}$$

with $\dot{\hat{\alpha}}$ being the changing rate of the estimated $\hat{\alpha}$ with respect to the time, and $\bar{\alpha}$ representing the user-designed bound. With the fault detection alarm, a small changing rate of $\hat{\alpha}$ activates the fault accommodation step and thus leads to the calibration of the measured faulty signal, such that

$$\tilde{\omega}_{\mathrm{r}}^* = \frac{\tilde{\omega}_{\mathrm{r}}}{\hat{\alpha}}, \tag{22}$$

with $\tilde{\omega}_{\mathrm{r}}^*$ denoting the calibrated rotor speed signal.

Afterwards, the calibrated rotor speed signal is fed back to the wind turbine controller to eliminate the effects of the sensor fault, as shown in Fig. 2. As a consequence of such an FTC action, the estimated factor $\hat{\alpha}$ is recovered to 1.

Table 1. Parameters of the iterative learning FTC method for the considered cases.

Parameter		Value
L	Learning rate	0.1
$\hat{\alpha}_0$	Initial value	1
$\bar{e}_U$	Threshold	0.01
$\bar{\alpha}$	Bound	0.005

4. CASE STUDY

This section presents a case study to illustrate the effectiveness of the proposed iterative learning FTC method for sensor fault accommodation. The National Renewable Energy Laboratory (NREL)'s 5MW reference wind turbine model (Jonkman et al., 2009) is considered in this paper. It is modelled as a first-order nonlinear system. The WSE-TSR tracking control scheme and the proposed iterative learning FTC method are implemented in Mathworks Simulink.

To evaluate the performance of the proposed method, a turbulent wind profile with a mean wind speed of 9 m/s with a turbulence intensity (TI) = 5% is simulated in the case study. The simulation duration is 1200 s with a time step of 0.01 s. To simulate the faulty condition, a rotor speed sensor fault with the constant scaling factor $\alpha = 0.95$ is introduced at 500 s. Such a sensor fault is simulated in all the cases to illustrate the FTC performance. The parameters of the iterative learning FTC method are summarized in Table 1. In the following sections, first, only the fault detection and estimation function of the proposed method is activated for evaluation. Afterwards, the fault accommodation function is also enabled to demonstrate the overall FTC performance.

4.1 Fault detection and estimation

The main results are shown in Fig. 3. In detail, a comparison between the (unknown) real rotor speed ω_{r} and the measured rotor speed signal $\tilde{\omega}_{\mathrm{r}}$ is presented. Before 500 s, the wind turbine operates in a fault-free, nominal healthy condition. The sensor fault is introduced at 500 s, and the wind turbine operates at the faulty condition between 500 s and 1200 s, as indicated by a yellow background. It is evident from Fig. 3(c) that the measured rotor speed is scaled down due to the considered sensor fault. The real rotor speed, however, slightly increases, which leads to a significant difference between the real and measured faulty signals. As shown in Fig. 3(f), due to the biased REWS estimate, such a biased rotor speed signal leads to deviations between the real and estimated TSR set point, which results in degraded power production under the faulty condition in Fig. 3(d).

The performance of the proposed iterative learning method is shown in Fig. 3(a-b). The proposed FTC method is able to approximate the scaling factor online successfully. Some oscillations are observed in the learned $\hat{\alpha}$ due to the wind turbulence, which may cause uncertainties in such a learning procedure. Under the nominal condition, $\hat{\alpha}$ varies around 1 before 500 s, indicating no sensor fault at the rotor speed measurement. After 500 s, the scaling factor $\hat{\alpha}$ drops to around 0.95 close to the reference, implying good fault estimation performance. Since the learning er-

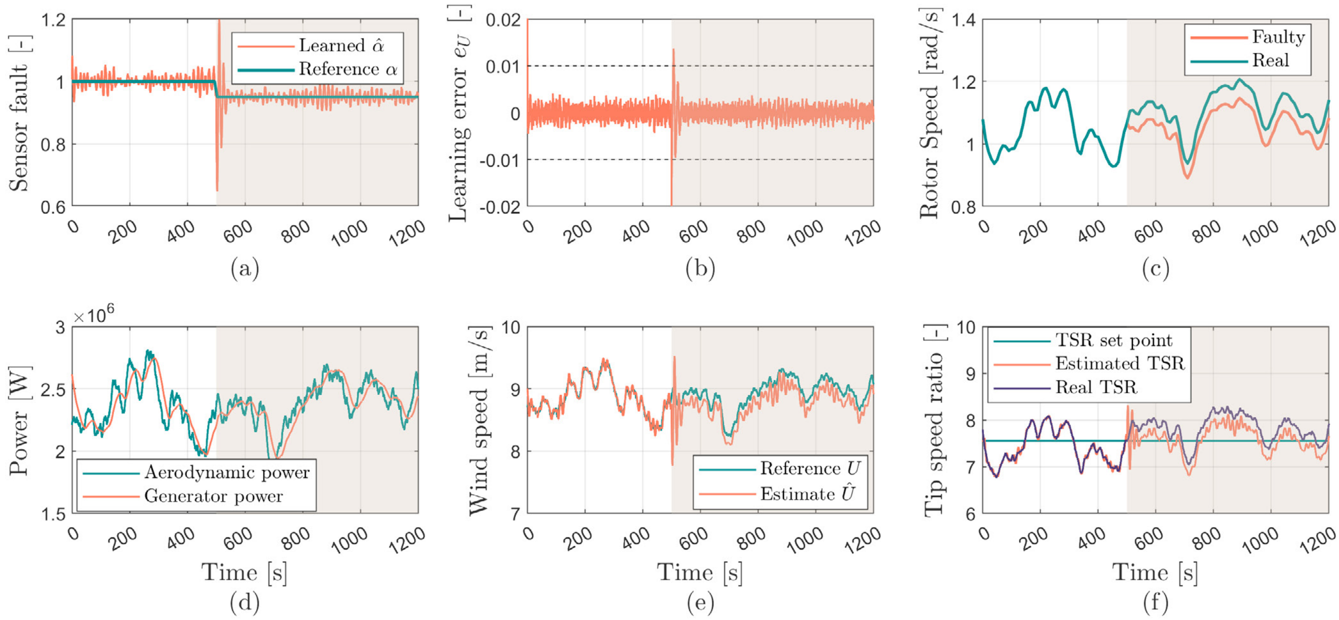

Fig. 3. Case study of the FTC method where only the fault detection and estimation step is activated. A turbulent wind condition with a mean wind speed of 9 m/s and TI of 5 % is considered. The iterative learning method is implemented online. The sensor fault occurs between 500 s and 1200 s as indicated by the olive background.

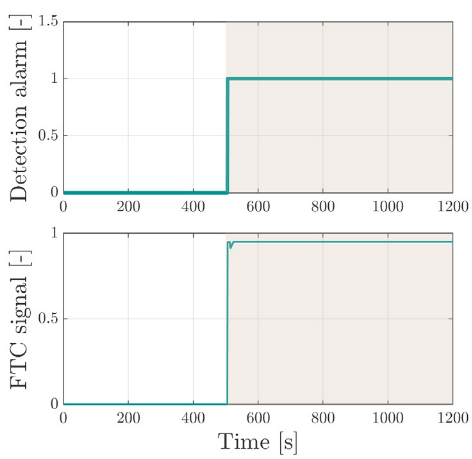

Fig. 4. Fault detection alarm and the fault-tolerant signal generated in the iterative learning FTC method where the fault accommodation is enabled.

ror crosses the designed threshold, as shown in Fig. 3(b), a sensor fault has been detected, which triggers the detection alarm at 506 s in Fig 4(a).

In summary, it can be concluded from Fig. 3 that the proposed algorithm can detect and estimate the multiplicative sensor fault automatically under turbulent wind conditions.

4.2 Enabling the fault accommodation

Based on the sensor fault information derived in the fault detection and estimation step, the fault accommodation step complements the FTC method by online calibrating the faulty signal induced by the sensor fault. This calibration will eliminate the effects of the sensor fault and thus increase the control system's resilience against the inaccuracy and uncertainties of the measurement. The same wind condition and the fault scenario are considered in this case study and exhibited in Fig. 5. Similarly, a rotor speed sensor fault is detected in the fault detection and estimation step, which triggers the detection alarm, as shown in Fig. 4(a). Once a consistent estimate of the scaling factor is obtained according to (22), the learned scaling factor, considered the FTC law, is fed back to the WSE-TSR tracking control scheme to calibrate the faulty signal of the rotor speed as seen in Fig. 4(b). Consequently, the effects of the sensor fault on the estimates of REWS and TSR are eliminated, as shown in Fig. 5(e-f). Because of the fault accommodation step, the wind turbine controller maintains its torque control performance in wind turbine operation even under faulty conditions. The learned scaling factor is then recovered to around 1, as demonstrated in Fig. 5(a).

In summary, the proposed method, including fault detection, estimation and accommodation steps, is a valuable addition to the current wind turbine control scheme. With the augmented iterative learning FTC method, the wind turbine controller is able to deal with the frequently occurring sensor fault and increases its resilience against the inaccuracy and uncertainties in the rotor speed measurement.

5. CONCLUSION

The combined wind speed estimator and tip speed ratio (WSE-TSR) tracking controller is widely used in wind turbines to regulate power production. Although very effective, this control scheme highly relies on the prior model information and a limited set of measurements. Inaccuracy in the measurements used in the control scheme will result in turbine operation away from the desired operating point. This suboptimal operation may lead to

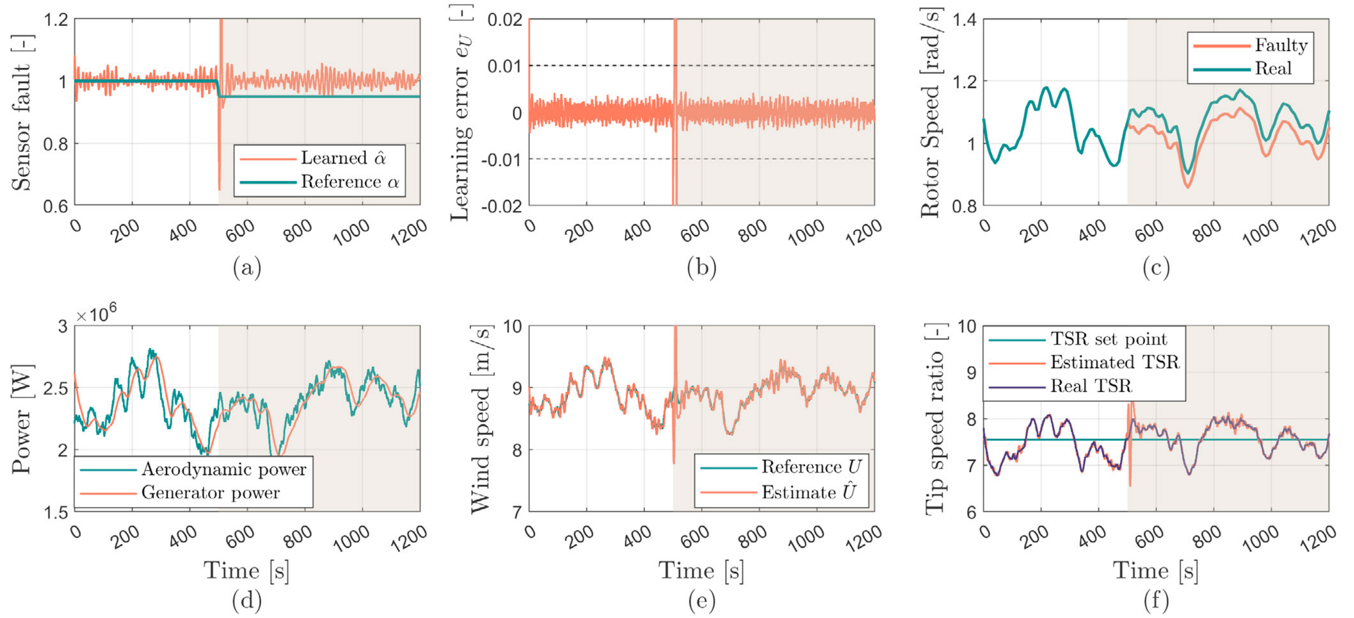

Fig. 5. Case study of the FTC method where the fault detection, estimation and accommodation steps are enabled. Similarly, a turbulent wind condition with a mean wind speed of 9 m/s and TI of 5 % is considered. The whole framework is implemented online. The sensor fault occurs between 500 s and 1200 s as indicated by the olive background.

degraded power production and, more severely, give rise to unstable operation. This paper proposes an iterative learning fault-tolerant control (FTC) method to tackle the sensor fault, which frequently occurs at the measured rotor speed signal. It leverages wind speed measurements and the inherent knowledge and structure of the wind turbine controller to detect, estimate and accommodate the potential sensor fault. With the iterative learning FTC method in the loop, the considered wind turbine control shows high resilience against measurement uncertainties. It is thus able to cope with the sensor fault under faulty conditions. Simulation results illustrate that the proposed method performs well in fault detection, estimation and accommodation. More importantly, the FTC based on the iterative learning method is achieved in an adaptive way, such that the impacts of the sensor fault can be eliminated shortly.

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