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A Generalized Observer for Estimating Fast–Varying Disturbances

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ABSTRACT In this paper, a generalized disturbance observer (GDO) is proposed for estimating a broad range of disturbances including fast-varying ones. The estimation error of the proposed GDO is proven to be ultimately bounded provided that an arbitrary r^{th} time derivative of disturbance is bounded. A broader range of disturbances can be estimated by the proposed GDO in comparison with the conventional disturbance observers (DO) or even recent fast-varying disturbance observers (FVDO) because conservative assumptions such as zero time-derivatives of disturbances are avoided. Furthermore, intuitive rules for gain-tuning and selecting the weighting matrices in the observer design are systematically presented. To validate the superiority of the proposed GDO to conventional FVDOs, comprehensive studies using the linear and nonlinear systems with different types of disturbances are conducted in the MATLAB/Simulink platform. In a specific application of wind energy conversion systems, the proposed GDO is employed to precisely estimate the aerodynamic torque. Then, a completed control system with a linear quadratic regulator (LQR) is designed and implemented to verify the final performance with the proposed GDO. The proposed observer-based LQR is proved to ultimately be bounded stable with superior performances to further validate the proposed GDO.

INDEX TERMS Disturbance observer, fast-varying disturbance, optimal control, uncertainties estimation, wind energy conversion system (WECS).

I. INTRODUCTION

Disturbance observers (DOs) have been widely used to estimate disturbances, uncertainties and noise [1], [2] due to their simplicity, transparence of design, and effectiveness. During last three decades, DO are extensively applied to a broad range of systems such as robot manipulators [3], [4], disk drivers [5]–[7], navigation control systems [8], air-breathing hypersonic vehicles [9], missiles control [10], and wind turbine [11].

In conventional DOs [3]–[8], [10], [11], the convergence of DOs was guaranteed with an assumption that disturbances are slowly varied in comparison with observer dynamics. Without this assumption, the convergence of estimation error was not assured. Unfortunately, in practice, disturbances usually have fast dynamics. As a result, the conventional DOs design associated with the slow-varying assumption does not satisfy the estimation accuracy and disturbance rejection performance.

Advanced DOs such as extended state observer (ESO) in active disturbance rejection control (ADRC) [12], [13], unknown input observer (UIO) [14], [15], and equivalent input disturbance (EID) estimator [16], [17] were introduced. Although these approaches were developed from the different bases and prospects, their stability analyses were still based on the key assumption that the first time-derivative of disturbance is zero. Recent works presented enhanced DOs such as adaptive DO for permanent magnet linear synchronous machines (PMLSMs) [18], nonlinear optimal DO for permanent magnet synchronous motors (PMSMs) [19] with high-performance of estimation and interesting characteristics. However, the aforementioned assumption is still required.

Fast-varying disturbance observers (FVDOs) were first introduced in [20] with the analysis in frequency domain, and further discussed in [21]–[23]. Although the frequency approaches are intuitive and simple, they are only applicable to a class of linear systems and unable to analyze the transient performance. Meanwhile, state-space approaches allow the transient behavior analysis such as investigated FVDOs in [9], [24]–[28]. Although the disturbance estimation performances are improved in some aspects, the problems encountered in these methods [9], [24], [25], [27], [28] are the lack of gain-tuning rules, which limit their applications to practical systems. In [26] and [28], the concept of multiple-integral observer was proposed with pole placement technique for gain selections. However, the information of derivative and higher-order derivatives of disturbances which are essential in mismatched disturbance rejection control, are not available.

Wind energy is one of the most promising renewable energy sources as it does not produce any pollutant during operation, other than requirements for maintenance. At each wind speed, there is an optimal operating point for turbine to capture the maximum power. Therefore, there is a desire for designing feedback control schemes to track the optimal reference of rotor speed associated with variable wind velocity [29]–[31]. However, it is difficult to precisely measure the wind speed via traditional cup-anemometers. Other estimation methods such as physical estimation methods in [32], [33], Gray models and Kalman filter [34]–[37], genetic algorithm [38] are either ineffective for short-term estimation, poor in estimation performance, or complicated. On the other hand, instead of estimating wind speed, the aerodynamic torque is observed [39]–[43]. In this approach, the conventional observer algorithms such as sliding-mode observers, robust observers are applied to estimate the aerodynamic torque based on the assumption that aerodynamic torque is slowly-varying. Unfortunately, as aerodynamic torque is proportional to the square of wind speed, this assumption is unreasonable. Although simulation and experimental results showed that with this assumption, the estimation performance is acceptable, there is no rigorous reasoning to guarantee the convergence of the observer.

Considering these issues, first, this paper proposes a generalized disturbance observer (GDO) for estimating disturbances including fast-varying ones. The gains of the proposed observer are systematically tuned via selecting appropriate value for elements of weighting matrices. The rules for choosing weighting matrices are also clearly presented for practice. Comparative studies are conducted to prove the superiority of the proposed observer cto conventional FVDO. For further verifying the effectiveness and feasibility of the proposed observer, it is applied to estimate the aerodynamic torque in the wind turbine (WT) optimal speed tracking problem. Hence, both the aerodynamic torque and wind speed measurements are avoided. The stability analysis of closed-loop control system with a linear quadratic regulator (LQR) is presented in detail. The comparative studies with conventional FVDOs and validation scenarios in WT application with the GDO based LQR schemes are carried out in MATLAB/Simulink to comprehensively verify the advantages of the proposed GDO. The contributions of this paper are summarized as follows:

1. A new theorem in the proposed GDO to estimate a broad range of disturbances by overcoming the drawbacks of existing observers [1]–[28], [25], [43]–[45] (i.e., the assumption that the first and/or higher order-time derivate of the disturbances is zero).
2. Further advantages of the proposed GDO in comparison with recent FVDOs:
   a. Better noise rejection ability (e.g., superior to the observer in [28]).
   b. Applicability into systems with unavailable state variables to solve the problem of recent methods which require all the state variables measurable [25], [45].
3. A proposed GDO-based LQR for systems with fast-varying disturbances, a theorem to analyze the overall stability of the proposed control system.
4. Practical application of the proposed GDO-based LQR to WT optimal speed tracking problem where the aerodynamic torque and speed reference are estimated by GDO.

II. GENERALIZED FAST-VARYING DISTURBANCE OBSERVER BASED ON OPTIMAL CONTROL APPROACH

A. PROBLEM STATEMENT

Consider the system [28], [44]

$$\begin{cases} \dot{x} = Ax + Bu + Dd \\ y = Cx \end{cases} \tag{1}$$

where $x \in R^n$, $u \in R^m$, $y \in R^s$, A, B, C, and D are known matrices, u is the control input , and d is the lump system disturbance, which may include parameter uncertainties, external disturbances, and system faults.

Assumption 1: The disturbance is continuous and its r^{th} time-derivative is bounded (i.e., $|d_i^{(r)}| \leq \varepsilon$ with $i = 0, 1, 2, \dots q$ where $d^{(r)}$ denotes the r^{th}-time derivative of the disturbance and ε is an unknown positive number).

It should be noted that this is the first time such a generalized assumption is presented for an observer design. With $r = 1$ and $\varepsilon = 0$, it turns out the common assumption in conventional DOs [1]–[8], [10] where the disturbance is considered as a slowly-varying variable or constant. With $r = 1$ and $\varepsilon \neq 0$, it turns out the assumption in [45]. With $r \geq 2$ and $\varepsilon = 0$, the common assumption is released as the varying level of disturbance is represented by the value of r via the order polynomial of time [9], [28], [44]. However, if the disturbances include the oscillation terms such as sinusoidal, the bound ε cannot be zero. Therefore, it is ineligible for the assumption on the disturbance as a finite r-order polynomial of time as in [9], [28], and [44]. In [25], the bound assumption is required for the disturbance and all of its time-derivatives, i.e., $\left|d_i^{(j)}\right| \leq \varepsilon$, with $i = 0, 1, 2, \dots q$; $j = 0, 1, 2, \dots r$.

Based on this assumption, the disturbance can be modeled as follows

$$\begin{cases} \dot{z} = Sz + Md^{(r)} \\ d = Nz \end{cases} \tag{2}$$

where $z = \left[\begin{array}{llll} d & \dot{d} & \ldots & d^{(r-1)} \end{array}\right]^T$, S, M, and N are the system matrices and have the following structures:

$$\begin{aligned} S &= \begin{bmatrix} 0_{q(r-1)\times q} & diag\left(W_1 \quad \cdots \quad W_{r-1}\right) \\ 0_{q\times q} & 0_{q\times q(r-1)} \end{bmatrix}, \\ W_i &= \begin{bmatrix} 0_{(r-1)\times 1} & I_{r-1} \\ 0 & 0_{1\times(r-1)} \end{bmatrix}, \\ M &= \left[0_{(r-1)\times q} I_q \right], \\ N &= \left[I_q \quad 0_{q\times(r-1)} \right]. \end{aligned} \tag{3}$$

B. GENERALIZED OBSERVER DESIGN

Combining (1) and (2), an extended system can be achieved and given by,

$$\begin{cases} \dot{\bar{x}} = \bar{A}\bar{x} + \bar{B}u + \bar{M}d^{(r)} \\ y = \bar{C}\bar{x} \end{cases} \tag{4}$$

where $\bar{x} = \left[\, z \; x \,\right]^T$,

$$\bar{A} = \begin{bmatrix} S & 0_{qr\times n} \\ (DN)_{n\times qr} & A \end{bmatrix}, \quad \bar{B} = \begin{bmatrix} 0_{qr\times m} \\ B \end{bmatrix},$$
$$\bar{C} = \left[0_{qr\times s} \quad C \right], \quad \bar{M} = \begin{bmatrix} M \\ 0_{n\times q} \end{bmatrix}$$

Lemma 1: If (A, C) is observable and $rank \begin{bmatrix} A & D \\ C & 0_{s\times q} \end{bmatrix} = n+q$, $\left(\bar{A}, \bar{C}\right)$ is observable for any positive integer value of r.

Proof: This proof can be completed similarity to that of *Theorem (i)* in [26].

The optimal observer for estimating disturbance and its derivatives is expressed as

$$d\hat{\bar{x}}/dt = \bar{A}\hat{\bar{x}} + \bar{B}u + L(y - \bar{C}\hat{\bar{x}}) \tag{5}$$

where control signal u is the function of x will be achieved from the output of the controller and $L = P_o\bar{C}^T R_o^{-1}$, with P_o is the solution of the following Riccati equation

$$\bar{A}P_o + P_o\bar{A}^T - P_o\bar{C}^T R_o^{-1}\bar{C}P_o + Q_o = 0 \tag{6}$$

In (6), Q_o is a symmetric positive semidefinite matrix and R_o is a symmetric positive definite matrix.

Based on the assumption, the error dynamics of the observer is obtained as follows:

$$d\tilde{\bar{x}}/dt = \left(\bar{A} - L\bar{C}\right)\tilde{\bar{x}} + \bar{M}d^{(r)} \tag{7}$$

where $\tilde{\bar{x}}$ is the estimation error defined as $\tilde{\bar{x}} = \bar{x} - \hat{\bar{x}}$.

Theorem 1: With the proposed optimal observer given in (5) and (6), the estimation error is bounded.

Proof: Consider the following Lyapunov function: $V\left(\tilde{\bar{x}}\right) = \tilde{\bar{x}}^T H\tilde{\bar{x}}$, where $H = P_o^{-1}$. Its time derivative along the error dynamics (7) is given by

$$\begin{aligned} \dot{V} &= \frac{d}{dt}\tilde{\bar{x}}^T H\tilde{\bar{x}} \\ &= 2\tilde{\bar{x}}^T\left(H\bar{A} - PC^T R^{-1} C\right)\tilde{\bar{x}} + 2\tilde{\bar{x}}^T H\bar{M}d^{(r)} \\ &= \tilde{\bar{x}}^T H\left(\bar{A}P_o + P_o\bar{A}^T - 2P_o\bar{C}^T R^{-1}\bar{C}P_o\right) \\ &\quad \times H\tilde{\bar{x}} + 2\tilde{\bar{x}}^T H\bar{M}d^{(r)} \\ &\le -\tilde{\bar{x}}^T HQ_oH\tilde{\bar{x}} + 2\tilde{\bar{x}}^T H\bar{M}d^{(r)} \\ &\le -\left\|\tilde{\bar{x}}\right\|\left(\lambda_{m1}\left\|\tilde{\bar{x}}\right\| - 2\left\|H\bar{M}\right\|\varepsilon\right) \end{aligned} \tag{8}$$

where λ_{m1} denote the smallest eigenvalue of HQ_oH.

Therefore, with an appropriated selection of Q_o and R_o and after a sufficiently long time, the norm of estimator is bounded by

$$\left\|\tilde{\bar{x}}\right\| \le \lambda_1 \tag{9}$$

where $\lambda_1 = 2\left\|H\bar{M}\right\|\varepsilon/\lambda_{m1}$.

Remark 1: It is noted that the upper bound λ_1 has an influence on the accuracy of the observer. However the upper bound λ_1 can be directly adjusted by tuning the weighting matrices Q_o, R_o to obtain the suitable λ_1. Therefore, the estimation error is regulated by choosing weighting matrices such that the reasonable accuracy of observer is guaranteed. Therefore, by referring to [46], the observer guarantees ultimate boundedness and uniform stability of an arbitrarily small ball centered at $\tilde{\bar{x}} = 0$.

C. FURTHER DISCUSSION

Discussion 1: In (1), for simplification, d is considered to be a scalar. However, the proposed GDO is not limited to this assumption. It is obvious that with d can be a multi-dimension vector, the design procedure of proposed GDO is remained the same, only dimensions of S, M, and N are required to be modified.

Discussion 2: The following nonlinear systems [28] is considered as

$$\dot{x} = f(x, u) + Dd. \tag{10}$$

The proposed GDO is also applicable by transforming (9) to (1):

$$\dot{x} = Ax + [f(x, u) - Ax] + Dd \tag{11}$$

where matrix A now is defined as $A = diag\left(a_1, a_2, \ldots, a_n\right)$ with its elements are designed parameters. Then GDO can be designed for (10) as in (5) by just replace the term $\bar{B}u$ by $[f(x, u) - Ax]$.

Discussion 3: The proposed observer in (5) is the Kalman-Bucy optimal observer which minimizes the performance index $E(\tilde{\bar{x}}^T\tilde{\bar{x}})$ representing the expectation value of $\tilde{\bar{x}}^T\tilde{\bar{x}}$ for the following perturbed model

$$\begin{cases} \dot{\bar{x}} = \bar{A}\bar{x} + \bar{B}u + \bar{M}d^{(r)} + p \\ y = \bar{C}\bar{x} + q \end{cases} \tag{12}$$

where p and q are independent white Gaussian noise signals with $E(p) = 0$, $E(q) = 0$, $E(pp^T) = Q_o$, and $E(qq^T) = R_o$.

Accordingly, the observer performance is mainly influenced by the system model if the measurements are noisy (R_o large) and the input noise is small (Q_o small). Therefore, L is small. This leads to a slow observer as measured by the location of its eigenvalues. However, if the measurements are good and the input noise intensity is large, the observer performance is dependent on the measurement. In this case, L is large, resulting in a fast observer with high bandwidth. Thus, by assuming that the measurement is good, the fast observer is desirable. The subsequent procedure summarizes the tuning process of the observer gain matrix L [47]:

1) Set Q_o and R_o as diagonal matrices with initial elements is set as one (i.e., initial guess of Q_o and R_o are identity matrices);
2) Gradually, increase elements of Q_o and decrease elements of R_o, then calculate L as in (5) and (6);
3) If the observer performance is not satisfied, return to step 2. Otherwise, quit.

Discussion 4: In recent FVDOs such as in [28], [45], and [25], all state variables need to be measurable in order to construct the observers. Meanwhile, in the proposed GDO, this drawback is solved. The observer is designed as long as the Lemma 1 is satisfied. In this context, both disturbance and the unavailable state(s) are estimated. In section III, this advantage will be discussed in detail.

Discussion 5: Finally, note that the proposed disturbance observer is applicable to any control law such as in [1]–[28], and [25], [39]–[45] to improve their overall control performance and extend range of applications. In section IV, a GDO-based LQR will be designed for WECSs.

III. COMPARING THE PROPOSED GDO TO CONVENTIONAL HIGH-ORDER OBSERVERS

A. COMPARING TO THE HIGH-ORDER DISTURBANCE OBSERVER IN [28] CONSIDERING A RAMP DISTURBANCE

In [28], the following system is considered:

$$\dot{x} = -2x + d \tag{13}$$

where d is a sawtooth waveform.

Then the disturbance observer (DOB) in [28] is constructed as follows

$$\begin{aligned} \dot{\hat{x}} &= -2x + \hat{d} \\ \dot{\hat{d}} &= \gamma_0 \left(x - \hat{x}\right) + \gamma_1 \int_0^t \left(x - \hat{x}\right) d\tau \end{aligned} \tag{14}$$

Note that in the form of (1), $A = -2, C = D = 1$ and it is easy to check that condition of Lemma 1 is satisfied. Also, the conventional DOB in (13) is designed with the assumption that $\ddot{d} = 0$. Thus, for a fair comparison, the proposed GDO with $r = 2$ is used for comparison that has the dynamics as

$$\begin{aligned} \dot{\hat{d}} &= \hat{d}_1 + l_1 \left(x - \hat{x}\right) \\ \dot{\hat{d}}_1 &= l_2 \left(x - \hat{x}\right) \\ \dot{\hat{x}} &= -2x + \hat{d} + l_3 \left(x - \hat{x}\right) \end{aligned} \tag{15}$$

where $L = \left[\, l_1 \; l_2 \; l_3 \,\right]^T$ is calculated from (6) with

$$\bar{A} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & -2 \end{bmatrix}, \quad \bar{C} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \tag{16}$$

Note that in this example, there is no controller included.

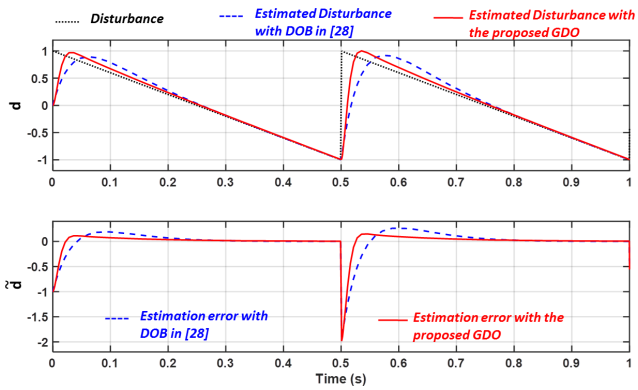

FIGURE 1. Comparative results for system (12) of the conventional DOB in [28] and the proposed GDO under the condition of case 1 (no noise).

Case 1 (No Noise): Fig. 1 shows the comparative simulation results of the DOB and proposed GDO with the following selected gains: $(\gamma_0, \gamma_1) = (40, 400)$ (the same as in [28]) and the weighting matrices:

$$Q_o = 10^2 \times diag\left(10^4 \quad 0.8 \quad 250\right), \quad R_o = 10^{-2}.$$

It is observed that although both methods achieve zero steady-state error; however, the proposed GDO provides shorter settling time.

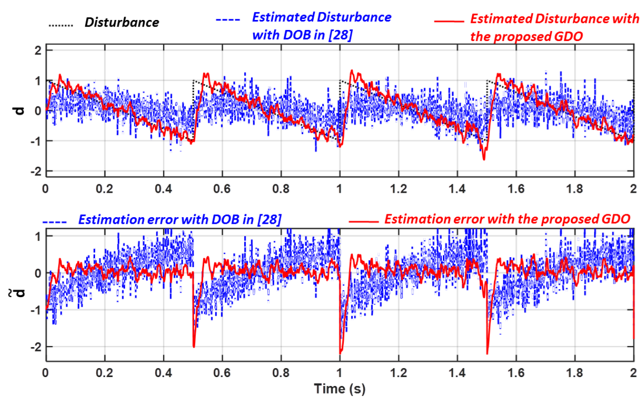

FIGURE 2. Comparative results for system (12) of the conventional DOB in [28] and the proposed GDO under the condition of case 2 (with noise).

Case 2 (With Noise): Assuming that there is a sample Gaussian noise with frequency of 1000, zero-mean, and standard deviation of 0.01 is included in the measured state. For the conventional DOB, In order to deal with the noise, the first equation of (13) is revised to $\dot{\hat{x}} = -2x + \hat{d} + k\left(x - \hat{x}\right)$. The gains of the conventional DOB is $(k, \gamma_0, \gamma_1) = (100, 40, 400)$ [28]. Also, the weighting matrices of the proposed GDO are the same as case 1. Fig. 2 shows the comparative results of this conventional DOB in [28] and the proposed GDO considering the noise. It is easy to see that the proposed GDO can mitigate the noise more effectively.

B. COMPARING TO THE EXTENDED DISTURBANCE OBSERVER IN [25] WITH A COMPLEX DISTURBANCE

Consider the following systems [45], [25],

$$\begin{cases} \dot{x}_1 = x_2 + d \\ \dot{x}_2 = -2x_1 - x_2 + e^{x_1} + u \end{cases} \tag{17}$$

where

$$\begin{cases} d = \frac{1}{2}x_1^2 + x_1 \sin(2t) + 0.2x_2 + \frac{t}{6} + \sin^2(2t) \\ \quad - \cos(2t) \text{ for } t < 2 \\ d = \frac{1}{2}x_1^2 + x_1 \sin(2t) + 0.2x_2 + \frac{t}{6} + \sin^2(2t) \\ \quad - \cos(2t) + 1 \text{ for } t \geq 2 \end{cases} \tag{18}$$

1) WITH ALL STATES ARE AVAILABLE

The second-order extended disturbance observer (EDO) in [25], is constructed as,

$$\begin{aligned} \hat{d} &= p_{11} + l_{11}x_1 \\ \dot{p}_{11} &= -l_{11}\left(x_2 + \hat{d}\right) + \hat{d}_1 \\ \hat{d}_1 &= p_{12} + l_{12}x_1 \\ \dot{p}_{12} &= -l_{12}\left(x_2 + \hat{d}\right) \end{aligned} \tag{19}$$

It should be noted that, in (18), only the first equation of the system (17) is considered for forming the EDO. Also, this conventional EDO is designed with the assumption that $\left|d^{(j)}\right| \leq \varepsilon$, with $j = 0, 1, 2$. Thus a fair comparison, the proposed GDO is designed by only using the first equation of (18) with $r = 2$. In the form of (1), $A = 0$, $C = D = 1$ and it is easy to check that the condition of Lemma 1 is satisfied. Then, the dynamics of the proposed GDO in this case is given as,

$$\begin{aligned} \dot{\hat{d}} &= \hat{d}_1 + l_1\left(x_1 - \hat{x}_1\right) \\ \dot{\hat{d}}_1 &= l_2\left(x_1 - \hat{x}_1\right) \\ \dot{\hat{x}}_1 &= x_2 + \hat{d} + l_3\left(x_1 - \hat{x}_1\right) \end{aligned} \tag{20}$$

where $L = \left[\, l_1 \; l_2 \; l_3 \,\right]^T$ is calculated from (6) with

$$\bar{A} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}, \quad \bar{C} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \tag{21}$$

Fig. 3 demonstrates the comparative simulation results of these two observers. Fig. 3 (a) illustrates the waveforms of the state x_1 and estimation errors of two observers. Fig. 3 (b) is the zoomed-in results of the lower plot in Fig. 3 (a). It is noted that these results are achieved by using the same controller as in [25] as

$$u = 2x_1 + x_2 - e^{x_1} - 5\left(x_2 + \hat{d}\right) - 50\left(x_2 + cx_1 + \hat{d}\right). \tag{22}$$

The gains of observers are tuned as follows:

$$\begin{aligned} &(l_{11}, l_{12}) = (100, 20), \\ &Q_o = 10^3 \times diag\left(10^3, 10, 1\right), \quad R_o = 10^{-2}. \end{aligned}$$

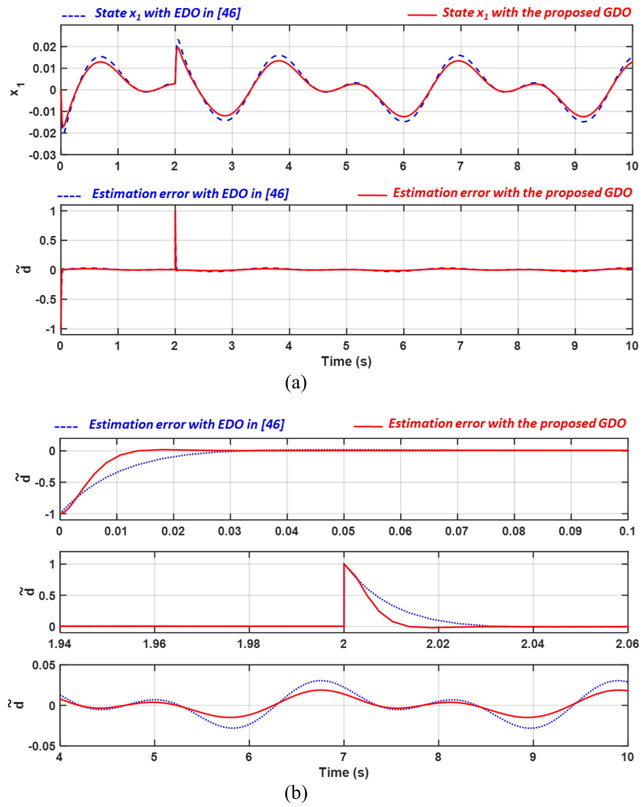

FIGURE 3. Comparative results for system (16) of the conventional EDO in [25] and the proposed GDO with $r = 2$ in case both x_1 and x_2 is measurable. (a) waveforms of state variable (x_1) and estimation error ($\tilde{d}$) for the time range from 0 sec to 10 sec. (b) Zoomed-in results of estimation error.

It is observed that the proposed GDO can give faster responses and smaller steady-state error of estimation and consequently, it results in smaller steady-state error of tracking error.

2) WITH ONLY STATE x_1 IS AVAILABLE

It is easy to see that the observer (18) and controller (21) in [25] for the system (16) require the information of x_2. With only x_1 is measurable, the EDO-based controller in [25] is inapplicable. However, we will show that with this condition, our proposed EDO is applicable and utilized to estimate both d and x_2. In this case, (1) can be transform to

$$A = \begin{bmatrix} 0 & 1 \\ -2 & -1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \end{bmatrix}, \; D = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{23}$$

So the rank of observable matrix

$$rank\,(Ob) = rank\left(\begin{bmatrix} C \\ CA \end{bmatrix}\right) = rank\left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right) = 2,$$

and $rank\left(\begin{bmatrix} A & D \\ C & 0 \end{bmatrix}\right) = rank\left(\begin{bmatrix} 0 & 1 & 1 \\ -2 & -1 & 0 \\ 1 & 0 & 0 \end{bmatrix}\right) = 3.$

It means the condition of Lemma 1 is satisfied. Thus, $\left(\bar{A}, \bar{C}\right)$ is observable any positive integer value of r. With the estimated value of x_2, the controller (21) is available by

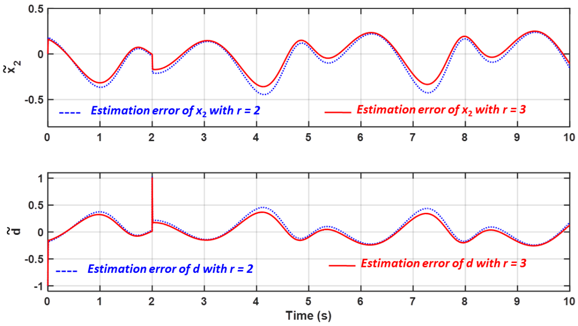

FIGURE 4. **Performance of the proposed GDO for system (16) with $r = 2$ and 3 in case only x_1 is measurable.**

replacing x_2 by $\hat{x}_2$. This controller is used for the simulation studies in this case. The observer laws are constructed similarly as previous case. Fig. 4 demonstrates the estimation error of x_2 and d with r = 2 and 3. Here, the weighting matrices for $r = 2$ are

$$Q_{o2} = 10^3 \times diag\left(10^3, 10, 1, 10^3\right), \quad R_{o2} = 10^{-2};$$

and for $r = 3$, the matrices are:

$$Q_o = 10^3 \times diag\left(10^3, 10, 10, 1, 10^3\right), \quad R_o = 10^{-2}.$$

As seen from Fig. 4, the estimation errors with $r = 3$ are slightly smaller than those with $r = 2$.

IV. GDO BASED LQR FOR TRACKING CONTROL OF WIND ENERGY CONVERSION SYSTEMS

A. WIND ENERGY CONVERSION SYSTEM MODELLING

The dynamics of wind energy conversion systems (WECSs) [31], [48], can be expressed as,

$$\begin{cases} \dot{\theta}_r = \omega_r \\ J_t\dot{\omega}_r = T_a - K_t\omega_r - B_t\theta_r - T_g \\ L_s\dot{T}_g = -R_sT_g + u \end{cases} \tag{24}$$

where θ_r is the angular position of the rotor, ω_t is angular velocity of the rotor, T_a is aerodynamic torque, T_g is electromagnetic torque of generator, u is the control input, J_t is the equivalent inertial constant, K_t is equivalent external damping constant, B_t is equivalent stiffness constant, and L_s and R_s are the lumped inductance and resistance of the generator.

The equation in (23) can be rewritten in the state-space form as (1) with

$$x = \begin{bmatrix} \theta_r \\ \omega_r \\ T_g \end{bmatrix}, \quad A = \begin{bmatrix} 0 & 1 & 0 \\ -a_1 & -a_2 & -a_3 \\ 0 & 0 & -a_4 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \\ b \end{bmatrix},$$
$$D = \begin{bmatrix} 0 \\ d_1 \\ 0 \end{bmatrix}, \quad d = T_a, \; C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{25}$$

and

$$a_1 = \frac{B_t}{J_t}, \; a_2 = \frac{K_t}{J_t}, \; a_3 = \frac{1}{J_t}, \; a_4 = \frac{R_s}{L_s}, \; b = \frac{1}{L_s}, \; d_1 = \frac{1}{J_t}. \tag{26}$$

The aerodynamic torque is calculated as,

$$T_a = P_a/\omega_t \tag{27}$$

where P_a is the aerodynamic power that the wind turbine extracts from the wind which is given as follows

$$P_a = \frac{1}{2}\rho\pi R^2 C_p\left(\lambda, \beta\right) v^3 \tag{28}$$

where ρ is the air density, R is the WT rotor radius, v is the wind speed, and the power coefficient $C_p(\lambda, \beta)$ represents the turbine efficiency to convert the kinetic energy of the wind into mechanical energy. This coefficient depends on the shape and geometrical dimensions of the turbine and it is a nonlinear function of the pitch angle of the blades β and the tip-speed ratio

$$\lambda = \frac{\omega_r R}{v}. \tag{29}$$

According to (27), the captured power is linearly proportional to coefficient C_p, which is reached its maximum value C_{pmax} at the optimal tip-speed ratio λ_{opt}. For a given wind turbine, λ_{opt} is a constant value. Therefore, maximum captured power is achieved by tracking the optimum reference of rotor speed given by:

$$\omega_{ref} = \frac{\lambda_{opt}}{R}v. \tag{30}$$

For this problem, it is assumed that the wind speed v is unknown. Then consequently, ω_{ref} and T_a are unknown. According to (26), (27), and (29) wind speed, wind speed reference, and aerodynamic torque can be calculated if one of them is known. So if one of them is estimated, the others are achievable. In this paper, the proposed GDO in section II.B is used to estimate aerodynamic torque with the parameters given in (23).

B. LQR DESIGN FOR OPTIMUM REFERENCE TRACKING

A LQR will be proposed for WT in this subsection. The WT system (23) and (24) can be transformed to the following form:

$$\dot{x} = Ax + B_c\left(u - u_c\right) \tag{31}$$

where $x = \left[\tilde{\theta}_r \; \tilde{\omega}_r \; \tilde{T}_g\right]^T, B_c = \left[0 \; 0 \; b\right]^T$; $\tilde{\theta}_r$ is the tracking error of angular position, $\tilde{\omega}_r$ is the tracking error of angular velocity, $\tilde{T}_g$ is the tracking error of the electromagnetic torque, u_c is the compensating terms of control inputs, respectively. They are defined as follows:

$$\begin{aligned} \tilde{\theta}_r &= \theta_r - \theta_{ref}; \quad \tilde{\omega}_r = \omega_r - \omega_{ref}; \; \tilde{T}_g = T_g - T_{ref}; \\ \theta_{ref} &= \int \omega_{ref}\, dt; \\ T_{ref} &= \frac{1}{a_3}\left(d_1T_a - \dot{\omega}_{ref} - a_1\theta_{ref} - a_2\omega_{ref}\right); \\ u_c &= -\frac{1}{b}\left(\dot{T}_{ref} + a_4T_{ref}\right). \end{aligned} \tag{32}$$

where θ_{ref} is the speed reference of angular position, and T_{ref} is the reference of electromagnetic torque. As a_3 and b are calculated as in (25) with J_t and L_s always positive numbers, calculations of T_{ref} and u_c as in (31) are always feasible. Noted that u_c is achieved through some transformation in order to include all the terms which cannot be expressed as functions of state variable x.

Define the following linear quadratic performance index:

$$J(x,u) = \int_0^\infty \left(x^T Qx + u^T Tu\right) \tag{33}$$

where $Q \geq 0$ and is an 3×3 matrix, $T > 0$ and is a scalar.

To minimize this performance index, a LQR is proposed as follows [49],

$$u = u_c - Kx \tag{34}$$

where $K = R^{-1}B^T P$ is the gain matrix of the controller and P is the positive-definite solution of following algebraic Riccati equation,

$$PA + A^T P - PB_c T^{-1} B_c^T P + Q = 0 \tag{35}$$

The gain tuning rule for LQR can be found in detail in [49] and [50].

Theorem 2: With the control law in (34), the state vector x in the system (23), (24) exponentially converges to zero.

Proof: Select the following Lyapunov function:

$$V(x) = x^T Px \tag{36}$$

So $V(x)$ is positive-definite and radially unbounded. From (23), (24), and (35), the time derivative of V satisfies,

$$\begin{aligned}\dot{V}(x) &= \frac{d}{dt}x^T Px\\ &= 2x^T P(A+BK)x\\ &= 2x^T P\left(A - BT^{-1}B^T P\right)\\ &= x^T P\left(PA + A^T P - 2PBT^{-1}B^T P\right)x\\ &\leq -x^T Qx\end{aligned} \tag{37}$$

It means the time-derivative of V is negative for all of non-zero x. It implies that x exponentially converges to zero.

C. GDO BASED TRACKING CONTROL

It is easy to check that the condition of Lemma 1 is satisfied. With the estimated disturbance $\hat{d} = \hat{T}_a$ by using GDO presented in previous section and the system as in (23), (24) according to (26)-(28), the estimation of rotor speed reference can be achieved by,

$$\hat{\omega}_{ref} = \sqrt{\frac{\hat{T}_a}{k_{opt}}} \tag{38}$$

where $k_{opt} = \frac{1}{2}\rho\pi R^5 C_{pmax}/\lambda_{opt}^3$.

Based on the estimated aerodynamic torque $\hat{T}_a$, the tracking error and compensating terms are now expressed as

$$\begin{aligned}&\hat{\tilde{\theta}}_r = \theta_r - \hat{\theta}_{ref}; \quad \hat{\tilde{\omega}}_r = \omega_r - \hat{\omega}_{ref}; \quad \hat{\tilde{T}}_g = T_g - \hat{T}_{ref};\\ &\hat{\theta}_{ref} = \int \hat{\omega}_{ref}\, dt;\\ &\hat{T}_{ref} = \frac{1}{a_3}\left(d_1\hat{T}_a - \dot{\hat{\omega}}_{ref} - a_1\hat{\theta}_{ref} - a_2\hat{\omega}_{ref}\right);\\ &u_c = -\frac{1}{b}\left(\dot{\hat{T}}_{ref} + a_4\hat{T}_{ref}\right).\end{aligned} \tag{39}$$

Control law (34) now becomes

$$u = \hat{u}_c - K\hat{x} \tag{40}$$

where $\hat{x} = \left[\hat{\tilde{\theta}}_r \; \hat{\tilde{\omega}}_r \; \hat{\tilde{T}}_g\right]^T$.

Then, from (38), the following equations are achieved,

$$\begin{aligned}\hat{x} &= x + Fx_e\\ \hat{u}_c &= u_c + Gx_e\end{aligned} \tag{41}$$

where

$$x_e = \begin{bmatrix} e & \dot{e} & \ddot{e}\end{bmatrix}^T, \quad e = T_a - \hat{T}_a,$$

$$F = \begin{bmatrix} n_1 & 0 & 0\\ n_2 & 0 & 0\\ n_3 & n_4 & 0\end{bmatrix}, \quad G = \begin{bmatrix} g_1 & g_2 & g_3\end{bmatrix},$$

$$n_1 = \frac{2\left(T_a + \hat{T}_a + \sqrt{T_a\hat{T}_a}\right)}{3\sqrt{k_{opt}}\left(\sqrt{T_a} + \sqrt{\hat{T}_a}\right)}, \quad n_2 = \frac{1}{\sqrt{k_{opt}}\left(\sqrt{T_a} + \sqrt{\hat{T}_a}\right)},$$

$$n_3 = \frac{1}{a_3}\left(d_1 - a_2h_2 - a_1h_1 + \frac{\dot{\hat{T}}_a}{2\sqrt{k_{opt}T_a\hat{T}_a}(\sqrt{T_a} + \sqrt{\hat{T}_a})}\right),$$

$$n_4 = \frac{1}{2a_3\sqrt{k_{opt}T_a}}, \quad g_1 = -\frac{1}{b}\left(\dot{n}_3 + a_4n_3\right),$$

$$g_2 = -\frac{1}{b}\left(n_3 + a_4n_4 + \dot{n}_4\right), \quad g_3 = -\frac{n_4}{b_1}.$$

D. STABILITY ANALYSIS OF CLOSED-LOOP SYSTEM

In order to analyze the stability of the system, (40) is rewritten based on (41) as

$$u = u_c - Kx + Ex_e \tag{42}$$

where $E = KF + G$.

On the other hand, we have

$$x_e = U\tilde{\bar{x}} \tag{43}$$

where $U = \left[I_3 \; 0_{3\times(n+r-3)}\right]$. Note that in this case, $n = 3$.

Theorem 3: The state vector x and the estimation vector $\tilde{\bar{x}}$ exponentially converges to zero.

Proof: Consider the following Lyapunov function:

$$V\left(x, \tilde{\bar{x}}\right) = x^T Px + \gamma\tilde{\bar{x}}^T H\tilde{\bar{x}} \tag{44}$$

where γ is a positive constant.

Then its time derivative is given by,

$$\begin{aligned}&\dot{V}(x, x_e)\\ &= 2x^T P(Ax + B_cu - B_cu_c) + 2\gamma\tilde{\bar{x}}^T H\left(\bar{A} - L\bar{C}\right)\tilde{\bar{x}}\end{aligned}$$

$$= 2x^T P \left(Ax - B_c Kx + B_c EU\tilde{\bar{x}}\right) + 2\gamma \tilde{\bar{x}}^T H \left(\bar{A} - L\bar{C}\right) \tilde{\bar{x}} + 2\gamma \tilde{\bar{x}}^T H\bar{M}d^{(r)} \leq -x^T Qx + 2x^T PB_c EU\tilde{\bar{x}} - \gamma\tilde{\bar{x}}^T HQ_o H\tilde{\bar{x}} + 2\gamma\tilde{\bar{x}}^T H\bar{M}\varepsilon \quad (45)$$

We further denote $x_a = \left[\, x \; \tilde{\bar{x}} \,\right]^T$, so

$$x = T_1 x_a, \quad \tilde{\bar{x}} = T_2 x_a \quad (46)$$

where $T_1 = \left[\, I_n \; 0_{n\times(n+r)} \,\right]$, $T_2 = \left[\, 0_{(n+r)\times n} \; I_{(n+r)} \,\right]$.
Then,

$$\begin{aligned} &-x^T Qx + 2x^T PB_c EU\tilde{\bar{x}} - \gamma\tilde{\bar{x}}^T HQ_o H\tilde{\bar{x}} + 2\gamma\tilde{\bar{x}}^T H\bar{M}\varepsilon \\ &= -x_a^T T_1^T QT_1 x_a + 2x_a^T T_1^T PB_c EUT_2 x_a - \gamma x_a^T T_2^T HQ_o HT_2 x_a + 2\gamma x_a^T T_2^T H\bar{M}\varepsilon \\ &\leq -\lambda_{m2}\left\|x_a\right\|^2 + 2\gamma\left\|T_1^T PB_c EUT_2\right\| \cdot \left\|x_a\right\|^2 + 2\gamma\varepsilon\left\|T_2^T H\bar{M}\right\|\left\|x_a\right\| \\ &= -\left\|x_a\right\|\left[\left(\lambda_{m2} - 2\gamma\left\|T_1^T PB_c EUT_2\right\|\right)\left\|x_a\right\| - 2\gamma\varepsilon\left\|T_2^T H\bar{M}\right\|\right] \end{aligned} \quad (47)$$

where λ_{m2} denote the smallest eigenvalue of $(T_1^T QT_1 + \gamma T_2^T HQ_o HT_2)$. It is easy to see that we can always choose γ to ensure that $\left(\lambda_{m2} - 2\gamma\left\|T_1^T PB_c EUT_2\right\|\right) > 0$. So with an appropriated selection of Q_o, R_o, Q, R. After a sufficiently long time, $\|x_a\|$ is bounded as

$$\|x_a\| \leq \lambda_2 \quad (48)$$

where $\lambda_2 = 2\gamma\varepsilon\left\|T_2^T H\bar{M}\right\| / \left(\lambda_{m2} - 2\gamma\left\|T_1^T PB_c EUT_2\right\|\right)$.

[1] Therefore, the state vector x and the estimation vector $\tilde{\bar{x}}$ are ultimately bounded and the bounds can be lowered by appropriately selecting of the weighting matrices of controller and observer. Thus the stability of the GDO-based LQR is proven in the sense of [46].

E. SIMULATION VERIFICATION

In this section, the simulation studies will be done with the following parameters [35], [48]: $J_t = 16, B_t = 52, K_t = 3, L_s = 0.01, R_s = 0.01, R = 21.65, \rho = 1.29$, and $C_{pmax} = 0.4291$ at $\lambda_{opt} = 8.1$. Fig. 5 shows the profile of the wind velocity.

The weighting matrices of LQR are selected as follows: $Q = diag\left(1, 10^3, 1\right)$ and $T = 10^{-3} \times diag\,(1, 1, 1)$. To verify the effectiveness of the proposed GDO, we will simulate with three case: $r = 1$, $r = 2$, and, $r = 3$. Accordingly, weighting matrices associated with these three values of r are tuned by referring to subsection II.C and achieved as follows,

$$Q_{o1} = diag(10^2, 10^3, 1, 1), \quad R_{o1} = 10^{-6} \times diag(1, 1, 1),$$
$$Q_{o2} = diag(10^2, 10^2, 10^3, 1, 1), \quad R_{o2} = R_{o1},$$
$$Q_{o3} = diag(10^2, 10^{2}, 10^2, 10^3, 1, 1), \quad R_{o3} = R_{o1}.$$

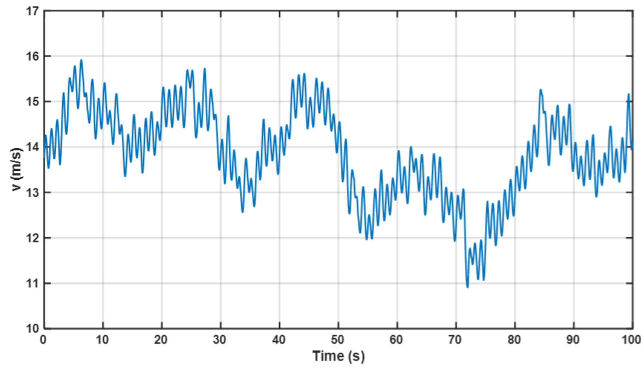

FIGURE 5. Wind velocity profile.

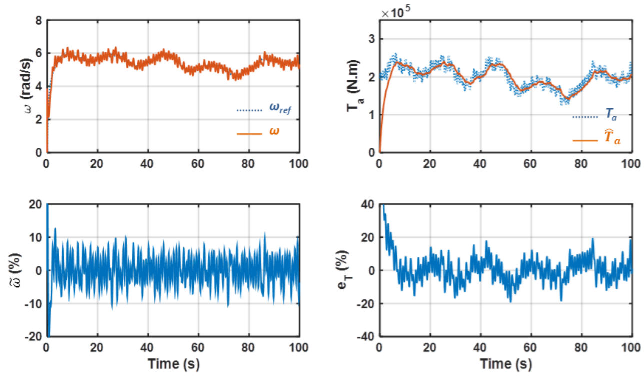

FIGURE 6. Control and estimation performance of the proposed GDO-based LQR with $r = 1$ for the WECS (23).

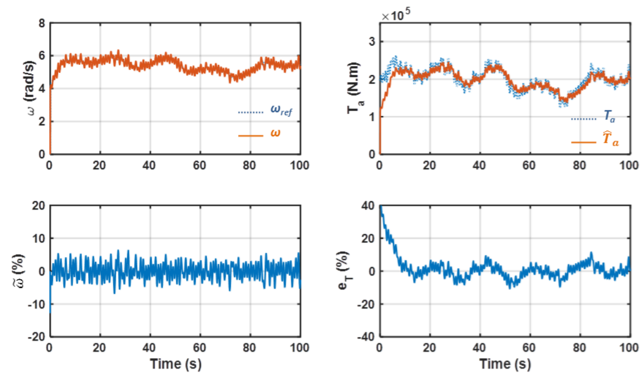

FIGURE 7. Control and estimation performance of the proposed GDO-based LQR with $r = 2$ for the WECS (23).

Figs. 6-8 illustrate the simulation results of proposed GDO-based LQR with $r = 1, 2$, and 3, respectively. In each figure, the waveform of the estimated angular velocity reference ($\hat{\omega}_{ref}$), the angular velocity response (ω_r), the aerodynamic torque (T_a), the estimated aerodynamic torque ($\hat{T}_a$), tracking error of angular velocity ($\tilde{\omega}$), and estimation error of the aerodynamic torque ($e_T = \hat{T}_a - T_a$) are shown. The tracking error and estimation error of three control schemes (three value of r) are included in one figure as illustrated in Fig. 9. As being observed from these figures, the best estimation

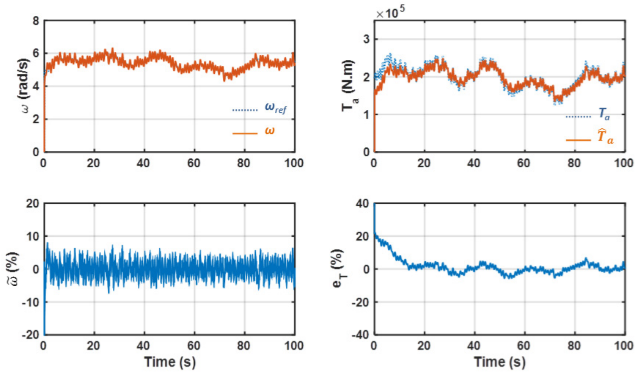

FIGURE 8. Control and estimation performance of the proposed GDO-based LQR with $r = 3$ for the WECS (23).

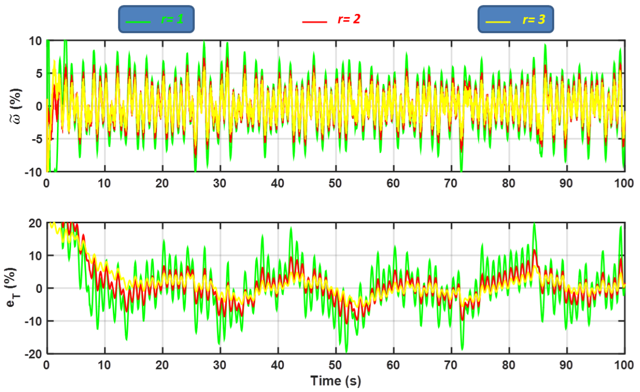

FIGURE 9. Comparative estimation errors of the proposed GDO-based LQR with $r = 1, 2, 3$ for the WECS (23).

performance is associated with $r = 3((e_T)_{max} = 20.2\%$, 11.8% and 6.7% for $r = 1$, 2, and 3, respectively). In other words, as the order of the observer increases, the aerodynamic torque is more precisely estimated. As a consequence, the estimation performance affects the tracking performance. Hence, the best tracking performance is also for the case $r = 3$ $((\tilde{\omega})_{max} = 10.3\%$, 7.2% and 6.1% for $r = 1$, 2, and 3, respectively).

V. CONCLUSION

This paper proposed a generalized disturbance observer called GDO for estimating a broad range of disturbances, including fast-varying ones. By using the proposed GDO, the common assumption that the first time-derivative of disturbance is slowly varied, is avoided. Also, our assumption loosens up the assumptions of conventional FVDOs to include more types of fast-varying disturbance. The proposed GDO has a very intuitive gain tuning rule which is straightforward and easy to implement. To validate the effectiveness of the proposed GDO, comparative studies with other conventional FVDOs has been conducted. Finally, the proposed GDO is applied to a WECS to estimate the aerodynamic torque while avoiding the measurement of wind velocity and aerodynamic torque. To verify by a specific application, a well-known LQR is combined with DGO to control the speed of the wind turbine. The overall stability analysis of the GDO-based LQR is also analyzed in detail and the advantageous performances are verified. The proposed GDO can be applied to any DO-based control scheme. Therefore, its applications are still opened which encourage more research works in the future.

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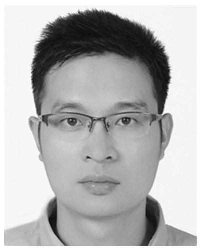

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