Adaptive PID Control of Standalone Wind Energy Conversion Systems

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Abstract: One of the most essential control tasks for standalone Wind Energy Conversion Systems (WECS) is to maximize the power conversion from wind. This task is normally achieved by the Maximum Power Point Tracking (MPPT) algorithms. However, such algorithms are simple and ineffective in satisfying additional complex requirements. Alternatively, the Proportional Integral Derivative (PID) control technique can be used for the optimal power conversion. However, the PID control is not effective in coping with the highly nonlinear, time-varying nature of WECS and stochastic change of wind. To overcome the PID control limitation, this paper presents an adaptive PID control design for standalone WECS, which is shown better than the traditional PID control in dealing with system changing conditions of WECS. The proposed adaptive strategy is validated by computer simulations.

Key–Words: PID control, Adaptive PID control, Lyapunov analysis, Standalone wind energy conversion systems, Optimal power conversion, Permanent magnet synchronous generator.

1 Introduction

Wind energy is one of the important renewable energy sources. Due to its clean and inexhaustible nature, wind energy has recently become central for both research and commercial developments. At present wind energy is a significant contribution of the world’s electrical generation [1, 2, 3]. Although electricity is accessible via central power grids, there are still remote areas where electrical power grids are unavailable due to physical (distance) and/or economical considerations. These locations have been facing a shortage of power supply. A promising sustainable solution is using standalone Wind Energy Conversion systems (WECS) which are connected to local loads. To cope with the stochastic behavior of wind, these WECS are constructed as energy systems consisting of a primary wind energy subsystem and other secondary energy subsystems, such as solar, battery, diesel generators, etc. to ensure constant power supply to the local loads [4].

The overall control of WECS is to balance the total power generation from the WECS and the total power demand of the local loads. Due to the presence of other sources of energy, it is required to coordinate power flows among energy sources within the WECS such that the power demand is met. Depending on the power demand and generation capacity from each energy source, different control strategies have been suggested to WECS [5]. Among energy subsystems in a WECS, the wind subsystem plays the primary role in generating and regulating the captured power. When the wind power generation is insufficient to the load power demand, the wind subsystem is controlled such that the power from wind is converted as much as possible according to the wind speed changes. Conversely, when the wind power generation is larger than the load power demand, the output power from the wind subsystem is regulated. The optimal power conversion control of standalone WECS has been studied using advanced control techniques in literature. For instance, the sliding mode control for a Permanent Magnet Synchronous Generator (PMSG)-based WECS was exploited in [6, 7]. Wang et al. in [8] reported an $H_{\infty}$ gain scheduling control for the maximizing power of a PMSG-based WECS. Authors in [9] employed the nonlinear output feedback linearization technique to design a nonlinear controller for a PMSG-based WECS.

In this paper, the focus is on the optimal power conversion of a standalone PMSG-based WECS subject to stochastic wind changes. An adaptive PID control (APID) strategy is proposed to achieve the optimal wind power extraction of the WECS. The APID strategy is based on the Lyapunov theory. The results are compared with that of the traditional PID control.

The paper is organized as follows. Section 2
describes a dynamical model for the optimal power conversion purpose of the standalone WECS. Section 3 presents the APID control technique, followed by the adaptive PID controller design for the standalone WECS in Section 4. The control performance of the proposed method is analyzed in Section 5 along with numerical simulation results. Finally, conclusions are included in Section 6.

2 Wind System Dynamical Model

An equivalent wind subsystem representative for the optimal power conversion is shown in Fig. 1. The model includes aerodynamics, drive-train dynamics, and generator dynamics.

The aerodynamics describes how wind power is converted into aerodynamic torque given as

\[ T_r = \frac{1}{2} \rho \pi R^2 V^2 C_Q(\lambda), \]  

(1)

where \( T_r \) is the aerodynamic torque, \( \rho \) is the air density, \( R \) is the radius of the wind rotor swept area, \( V \) is the wind speed, \( C_Q(\lambda) \) is the torque coefficient. As seen in (1) the torque varies according to the so-called tip-speed ratio \( \lambda \) (TSR) which is defined as

\[ \lambda = \frac{\omega_r R}{V}, \]  

(2)

where \( \omega_r \) is the wind rotor rotational speed. The torque coefficient \( C_Q(\lambda) \) in (1) can be approximated by the following sixth-order polynomial function of the TSR [9]

\[ C_Q(\lambda) = a_6 \lambda^6 + a_5 \lambda^5 + a_4 \lambda^4 + a_3 \lambda^3 + a_2 \lambda^2 + a_1 \lambda + a_0. \]  

(3)

The converted power is proportional to the power coefficient which is calculated as \( C_P(\lambda) = \lambda C_Q(\lambda) \) and has only one maximum value at the so-called optimal tip-speed ratio \( \lambda^* \) as shown in Fig. 2. Therefore, the maximum power conversion is only achieved if the wind subsystem is operated at the optimal TSR.

Figure 1: Equivalent wind energy conversion subsystem

The drive train is a mechanical power transmission unit which can be represented by a rigid (one-mass) model [9] as

\[ \dot{\omega}_g = \frac{\eta}{J_h} T_r - \frac{T_g}{J_h}, \]  

(4)

where \( J_h \) is the equivalent inertia transformed into the generator side, \( \eta \) and \( i \) are the gearbox efficiency and speed ratio respectively, \( T_r \) is the aerodynamic torque, and \( T_g \) is the generator electromagnetic torque.

The PMSG with the equivalent resistive load shown in Fig. 1 has the dynamical model in the synchronous frame or \( (d, q) \) frame as [9]

\[ \frac{di_d}{dt} = -\frac{R_s + R_L}{L_d + L_L} i_d + \frac{p(L_d - L_L)}{L_d + L_L} i_q \omega_g, \]  

(5)

\[ \frac{di_q}{dt} = -\frac{R_s + R_L}{L_q + L_L} i_q - \frac{p(L_d + L_L)}{L_q + L_L} i_d \omega_g \]  

\[ + \frac{p \Phi_m}{L_q + L_L} \omega_g, \]  

(6)

\[ T_g = p \Phi_m i_q, \]  

(7)

where \( i_d \) and \( i_q \) are the \( d \)- and \( q \)-components of the stator currents respectively; \( L_d \) and \( L_q \) are the \( d \)- and \( q \)-components of the stator inductances respectively; \( R_s \) is the stator resistance; \( R_L \) is the equivalent load resistance which is considered as the control input; \( L_L \) is the equivalent load inductance; \( p \) is the number of pole pairs; \( \Phi_m \) is the linkage flux; \( \omega_g \) is the generator speed; and \( T_g \) is the generator electromagnetic torque.

The complete nonlinear model of the PMSG-based wind subsystem is obtained by combining (1), (3) and (4)-(7).
3 Adaptive PID Control Method

Consider a Single Input Single Output (SISO) nonlinear system defined in the region \( D_x \in \mathbb{R}^n \) as

\[
\dot{x} = f(x) + g(x)u, \quad \text{where} \quad u \in \mathbb{R}^1 \quad \text{is the control input,} \quad y \in \mathbb{R}^1 \quad \text{is the system output,} \quad f(x) \in \mathbb{R}^n \quad \text{and} \quad g(x) \in \mathbb{R}^n \quad \text{are smooth vector fields,} \quad h(x) \in \mathbb{R}^1 \quad \text{is a scalar smooth function.}
\]

It is assumed the nonlinear system (8)-(9) has a relative degree \( r (r < n) \) at \( x_0 \in D_x \) and internal dynamics is stable, taking derivatives of the output \( y \) with respect to time up to \( r \) times gives

\[
y^{(r)} = \frac{L_f^r h(x) + L_g L_f^{r-1} h(x) u}{\alpha(x) \beta(x) \neq 0}, \quad (10)
\]

where \( L_f^r h(x) \) is the Lie derivative of \( h(x) \) along the direction of the vector field \( f(x) \) up to \( r \) times, \( L_g L_f^{r-1} h(x) \) is the Lie derivative of \( L_f^{r-1} h(x) \) a long the direction of the vector field \( g(x) \).

**Assumption 1** The function \( \beta(x) \) is positive (i.e. \( 0 < \beta(x) < \infty \) with \( \forall x \in D_x \)).

Choosing the state feedback linearization control:

\[
u^*(x) = \frac{1}{\beta(x)} (\alpha(x) + v), \quad (11)
\]

the input-output nonlinear relation (10) becomes linear as

\[
y^{(r)} = v, \quad (12)
\]

In practice, nonlinear functions \( \alpha(x) \) and \( \beta(x) \) are not known exactly. Therefore, adaptive schemes were proposed to approximate those functions using fuzzy systems [10]. However, such adaptive controls require all system states available, which is difficult to obtain in full. In this paper, the proposed APID eliminates the need of full access to system states.

### 3.1 PID Controller

The general form of PID control is given by

\[
u_{pid} = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{d}{dt} e(t), \quad (13)
\]

where \( K_p, K_i, \) and \( K_d \) are the proportional, integral, and derivative gains respectively, and \( e(t) \) is the error between the reference and output. The PID control in (13) can be rewritten by the form

\[
u_{pid} = \theta' \xi(e), \quad (14)
\]

where \( ' \) denotes transpose, \( \theta = [K_p \ K_i \ K_d]^T \) is the vector of gains, and \( \xi(e) = [e(t) \int_0^t e(\tau) d\tau \frac{d}{dt} e(t)]^T \) is the regressive vector of error.

The control problem is to drive the output \( y \) track a reference signal \( y_m \) (\( y_m \) is a smooth function). The feedback linearized control input \( v \) in (12) is defined as

\[
v = y_m^{(r)} + \bar{e}_s + \gamma e_s, \quad (15)
\]

where \( \gamma \) is a positive constant, \( \bar{e}_s \) and \( e_s \) are defined as

\[
e_s = e_o^{(r-1)} + k_1 e_o^{(r-2)} + ... + k_{r-1} e_o, \quad (16)
\]

\[
\bar{e}_s = e_s - e_o^{(r)} = k_1 e_o^{(r-1)} + ... + k_{r-1} e_o, \quad (17)
\]

\[
e_o = y_m - y, \quad (18)
\]

where \( e_s \) is the tracking error, \( e_o \) is the output error. Coefficients \( k_i \) are chosen such that following polynomial is Hurwitz

\[
E(s) = s^{r-1} + k_1 s^{r-2} + ... + k_{r-2} s + k_{r-1}. \quad (19)
\]

The ideal PID control input in (14) is approximated by

\[
\hat{u}_{pid}(e) = \theta_u^T \xi u(e), \quad (20)
\]

where \( \theta_u \) is updated online such that \( \hat{u}_{pid}(e) \) approaches \( u_{pid}^*(e) \). The optimal parameter vector is

\[
\theta_u^* = \arg \min_{\theta_u} \left\{ \sup_{x \in D_x} \left| \theta_u^T \xi u(e) - u_{pid}^*(e) \right| \right\}. \quad (21)
\]

Because \( u_{pid}^*(e) \) is approximated, there exists an unavoidable structural error \( \delta_u(e) \). Therefore the actual ideal control \( u_{pid}^*(e) \) is

\[
u_{pid}^*(e) = \theta_u^T \xi u(e) + \delta_u(e). \quad (22)
\]

The difference between the approximate control \( \hat{u}_{pid}(e) \) and ideal control \( u_{pid}^*(e) \) is

\[
\hat{u}_{pid}(e) - u_{pid}^*(e) = \bar{\theta}_u \bar{\xi} u(e) - \delta_u(e), \quad (23)
\]

where

\[
\bar{\theta}_u = \theta_u - \theta_u^* \quad (24)
\]

is the approximation error.
Assumption 2 The adaptive PID control is chosen such that the structural error is bounded \( |\delta_u(e)| \leq \delta_u \) with \( \forall e \in D_e \) and the upper bound \( \delta_u \) is known.

Due to the presence of the structural error, an additional supervisory control \( u_s \) is added to guarantee the closed-loop stability. Therefore the final control is

\[
u = \hat{u}_{\text{pid}} + u_s.
\]

### 3.2 Adaptive PID Law Design

The adaptive law designed based on an Lyapunov analysis is presented here.

Adding and subtracting \( \beta(x)u^*_{\text{pid}} \) into (10) gives

\[
y(r) = \alpha(x) + \beta(x)u^*_{\text{pid}} + \beta(x) \left[ u - u^*_{\text{pid}} \right],
\]

\[
v = \beta(x) \left[ u - u^*_{\text{pid}} \right].
\]

Combining (15), (18), (23), (25), and (26) gives

\[
e^{(r)}_o = y^{(r)}_o - y(r), \]

\[
e^{(r)}_o = y^{(r)}_o - v - \beta(x) \left[ u - u^*_{\text{pid}} \right], \]

\[
e^{(r)}_o = -\tilde{e}_s - \gamma e_s - \beta(x) \left[ \hat{u}_{\text{pid}} + u_s - u^*_{\text{pid}} \right], \]

\[
e^{(r)}_o = -\tilde{e}_s - \gamma e_s - \beta(x) \hat{u}^T \xi_u(e) + \beta(x) \delta_u(e) - \beta(x)u_s. \]

Combining (17) and (27) yields the error dynamic as

\[
\hat{e}_s + \gamma e_s = -\beta(x) \hat{u}^T \xi_u + \beta(x) \delta_u - \beta(x)u_s. \]

Considering a positive semidefinite quadratic Lyapunov function:

\[
V = \frac{1}{2\beta(x)} e^2 + \frac{1}{2} \hat{\theta}_u^T Q_u \hat{\theta}_u,
\]

where \( Q_u \) is a positive definite weighting matrix. Taking the derivative of \( V \) with respect to time, with the observation from (24) that \( \dot{\hat{u}}_u = \hat{\theta}_u \), yields

\[
\dot{V} = \frac{e_s}{\beta(x)} \hat{\theta}_u^T \xi_u - \frac{\beta(x)}{2\beta^2(x)} e^2 + \hat{\theta}_u^T Q_u \hat{\theta}_u.
\]

Substituting (28) into (30) produces

\[
\dot{V} = \frac{e_s}{\beta(x)} \left[ -\gamma e_s - \beta(x) \hat{u}^T \xi_u + \beta(x) \delta_u \right. \]

\[\left. -\beta(x)u_s \right] - \frac{\beta(x)}{2\beta^2(x)} e^2 + \hat{\theta}_u^T Q_u \hat{\theta}_u, \]

\[
\dot{V} = -\frac{\gamma e_s^2}{\beta(x)} - e_s u_s + e_s \delta_u + \hat{\theta}_u^T (Q_u \hat{\theta}_u - \xi_u e_s) \]

\[\left. - \frac{\beta(x)}{2\beta^2(x)} e^2. \right]

Choosing the adaptive law:

\[
\hat{\theta}_u = Q_u^{-1} \xi_u(e) e_s, \quad (32)
\]

and substituting (32) into (31) gives

\[
\dot{V} = -\gamma e_s^2 - e_s u_s + e_s \delta_u \]

\[\left. - \frac{\beta(x)}{2\beta^2(x)} e^2. \right]

Assumption 3 There exist positive lower bound and upper bound of \( \beta(x) \) (i.e. \( 0 < \beta \leq \beta(x) \leq \beta_0 \)).

Assumption 4 The velocity of \( \beta(x) \) is bounded (i.e. \( |\beta'(x)| \leq \beta_0 \)).

Combining (34) with assumptions 3 and 4 yields

\[
\dot{V} \leq -\gamma e_s^2 - e_s u_s + |e_s| \left( \delta_u + \frac{\beta(x)}{2\beta^2(x)} e_s \right), \quad (35)
\]

Choosing the supervisory control \( u_s \) as

\[
u_s = \left( \delta_u + \frac{\beta(x)}{2\beta^2(x)} e_s \right) \text{sgn}(e_s), \quad (36)
\]

and substituting (36) into (35) gives

\[
\dot{V} \leq -\frac{\gamma e_s^2}{\beta_0} \leq 0. \quad (37)
\]

Note that \( e_s \text{sgn}(e_s) = |e_s| \). It is seen from (29) and (37), the positive semidefinite Lyapunov function \( V \) has its negative semidefinite derivative \( \dot{V} \), therefore the closed-loop adaptive system is stable [11].

### 4 Adaptive Control Design for the Standalone WECS

In this section the adaptive PID control method presented in Section 3 is applied to the standalone nonlinear PMSG-based WECS given in (4)-(6). The control objective is to track the optimal generator speed reference \( \omega_g^* = \lambda^* R / iV \) in order to maintain the optimal tip-speed ratio \( \lambda^* \) as the wind speed \( V \) changes.

The adaptive PID control structure is shown in Fig. 3 where the adaptive controller is given in (20) with the adaptive law given in (32), and the supervisory controller is given in (36).

Simulation Results

The proposed method is validated by numerical simulations on MATLAB® and SIMULINK® environments with a 3KW standalone PMSG-based WECS whose system parameters given as [9]: \( \rho = 1.25 \text{ kg/m}^3 \), \( R = 2.5 \text{ m} \), \( i = 7 \), \( \eta = 1 \), \( J_h = 0.0552 \text{ kg.m}^2 \), \( L_d = L_q = 0.04156 \text{ H} \), \( p = 3 \), \( R_s = 3.3 \text{ } \Omega \), \( \phi_{m} = 0.4382 \text{ Wb} \), \( a_0 = 0.0061 \), \( a_1 = -0.0013 \), \( a_2 = 0.0081 \), \( a_3 = -9.7477 \times 10^{-4} \), \( a_4 = -6.5416 \times 10^{-5} \), \( a_5 = 1.3027 \times 10^{-5} \), \( a_6 = -4.54 \times 10^{-7} \), \( \lambda^* = 7 \). Lower and upper bounds in assumption 2, 3, and 4 are found as \( \bar{\delta}_u = 0.001 \), \( \beta = 1.545 \), and \( \beta_v = 30 \). The nonlinear PMSG-based WECS has the relative degree \( r = 2 \), so parameters for the error dynamics are chosen as \( \gamma = 15 \) and \( k_1 = 5 \). The control input is set bounded as \( 0 < u \leq 100 \). The stochastic wind profile is shown in Fig. 4. The control performance of the Adaptive PID Control (APID) proposed in this paper is compared with that of the standard PID Control (PID) designed by the built-in PID controller design toolbox in MATLAB® and SIMULINK®. The desired specifications were chosen as 8.96% of overshoot, 0.381 second of rise time, and 1.2 second of settling time. As a result, PID gains were obtained as \( K_p = 0.54255 \), \( K_i = 10.5036 \), and \( K_d = 0.000857 \).

Regarding the output tracking performance, Fig. 5 and 6 show both PID and APID track the output reference satisfactorily. However the APID provides better tracking than the PID does as seen from the Fig. 7 which indicates tracking errors.

Regarding the power conversion efficiency, Fig. 8 shows the APID is better than the PID in optimizing the power conversion. It is obvious that the APID stays constantly steady at the optimal tip-speed ratio value after the transient time. Meanwhile, the PID keeps oscillating around optimal tip-speed ratio value.

Conclusion

An adaptive PID control scheme was proposed in this paper. The control structure allows PID gains to be updated online according to a learning rule derived by the Lyapunov theory so that the controller is able to cope with time-varying changes of systems. The system close-loop stability is guaranteed by the addition of a sliding mode control. The effectiveness of the proposed control scheme was applied to maximize the
power conversion of a standalone wind energy conversion system. Comparisons were also carried out to show advantages of the adaptive PID control over the traditional PID with respect to tracking and optimal power conversion performances.

References:


