2011 50th IEEE Conference on Decision and Control and
European Control Conference (CDC-ECC)
Orlando, FL, USA, December 12-15, 2011

A Globally Convergent Wind Speed Estimator for Windmill Systems

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Abstract— **An estimator of the wind speed of a wind turbine coupled to a generator is proposed in this paper. Wind speed enters into the generator dynamics through a highly nonlinear function, hence we are confronted with a difficult problem of estimation of a nonlinearly parameterized system. To solve this problem we use the technique of immersion and invariance, recently introduced in the literature. It is assumed that the rotor speed and electrical torque of the generator are measured, which is the case for the machines typically used in this application. The result is of interest for the design of controllers of maximum power extraction, where the knowledge of the wind speed is necessary to express the control objective as a speed tracking problem. Detailed computer simulations are presented to assess the performances of the proposed estimator and a certainty equivalent proportional plus integral controller.**

Keywords Identification, nonlinearly parameterized systems, adaptive control, control of windmill systems.

I. INTRODUCTION

Wind power is becoming increasingly popular around the world due to its low footprint on the environment. Countries such as Denmark, Germany, Spain, the US and others have launched aggressive policies in order to drastically increase the wind power penetration in their energy portfolio for electricity generation [15]. It is often desirable to operate these systems at the point of maximum power extraction [3], [4], [6], [14]. To achieve this objective it is necessary to know the wind speed, which is usually not available for measurement.

Several publications have appeared in the literature attempting to control windmill systems without velocity measurement. To the best of our knowledge, none relies on the development of a *bona fide* parameter estimator that, as is well–known, is necessary for high–performance controller designs. The estimation of the wind speed is complicated because the unknown wind speed enters into the (mechanical) dynamics in a nonlinear way. Estimation of nonlinearly parameterized systems is a widely open research area—for which, besides practically questionable high–gain designs, almost no theoretical results are available in the literature. See [7] for a recent survey. The main contribution of the paper is the development of a wind speed estimator, which is proven to be consistent under a monotonicity assumption that is verified in several practical windmill models.

In [4] a provably stable adaptive controller to directly adjust the torque gain of a variable speed wind turbine is proposed. No attempt is made to estimate the wind speed, instead, concavity of the power coefficient function is assumed to adapt the gain of a *switching* torque—that intrinsically injects high gain in the loop. In [13] the well–known passivity–based and sliding mode control techniques are used to provide some guidelines for the controller design. Unfortunately, as indicated by the authors, the assumptions required by these techniques are not satisfied and the controller is designed invoking some approximations, with the wind speed (indirectly) reconstructed with an approximate differentiator.

The paper is organized as follows. Section II presents the dynamic model considered in the paper, followed by the estimation problem formulation in Section III and its solution in Section IV. Section V provides simulation results that illustrate the performance of the estimator and a proportional plus integral (PI) nonadaptive and (certainty equivalent) adaptive controllers. Finally, Section VI wraps–up the paper with some concluding remarks and future research work.

II. MATHEMATICAL MODEL OF THE WINDMILL SYSTEM

The windmill system considered in the paper consists of a wind turbine and a generator. The mechanical power available at the windmill shaft is given by[1]

$$P_w = \frac{1}{2}\rho A C_p(\lambda) v_w^3, \tag{1}$$

where ρ is the air density, A is the area swept by the blades, $C_p(\cdot)$ is the power coefficient, and v_w is the wind speed. The power coefficient is a function of the blades' tip speed λ, which is defined as

$$\lambda := \frac{r\omega_m}{v_w}, \tag{2}$$

with r the blades' radius and ω_m the shaft's rotational speed.

The shape of the function $C_p(\cdot)$ depends on the geometry of the windmill. Fig. 1 shows a typical curve that can be obtained from experimental measurements.[2] Clearly, the operating region for the blades tip speed is restricted to an interval $[0, \lambda_M],\ \lambda_M > 0$, such that

$$C_p(\lambda) \begin{cases} = 0 & \text{for} \quad \lambda = 0 \\ > 0 & \text{for} \quad \lambda \in (0, \lambda_M) \\ = 0 & \text{for} \quad \lambda = \lambda_M. \end{cases} \tag{3}$$

The mechanical dynamics of the generator are described by

"A full version of the paper has been submitted to CDC-ECC11"

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[1]All constants defined in the paper are positive. Interested readers are referred to [6], [13] for further details on models of windmill systems.

[2]In this, and all remaining plots, the function $C_p(\cdot)$ given in (22) is used.

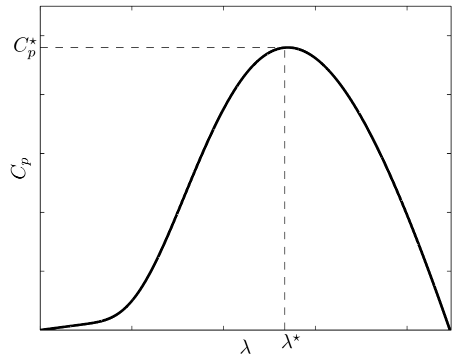

Fig. 1. Power coefficient for a typical windmill.

$$J\dot{\omega}_m = T_m - T_e. \tag{4}$$

where J is the rotor inertia, which is assumed known, T_e is the electrical torque and T_m is the mechanical torque applied to the windmill shaft, that readily follows from (1)

$$T_m = \frac{P_w}{\omega_m}.$$

Throughout the paper the following assumption —always verified in practice—is used.

Assumption 0 The motor rotates in the same direction with a minimal, positive, speed. That is, there exists $\omega_m^{\min} > 0$, such that

$$\omega_m(t) \geq \omega_m^{\min}, \tag{5}$$

for all $t \geq 0$.

For future reference it is convenient to define the key function

$$\frac{1}{J}T_m = \frac{\rho A}{2J}\frac{v_w^3}{\omega_m}C_p\left(\frac{r\omega_m}{v_w}\right) =: \Phi(\omega_m, v_w). \tag{6}$$

One practical scenario where the knowledge of v_w is essential is when we want to operate the system at the point of maximum power extraction. Namely,

$$\lambda^\star := \arg\max_{\lambda} C_p(\lambda),$$

which is typically known. Given v_w, the speed of maximum power extraction is defined using (2) as

$$\omega_m^\star := \frac{v_w}{r}\lambda^\star. \tag{7}$$

Given an estimate of v_w, say $\hat{v}_w$, the control task boils down to regulation of the shaft's speed ω_m around a reference speed

$$\omega_m^d = \frac{\hat{v}_w}{r}\lambda^\star. \tag{8}$$

In the nonadaptive case $\hat{v}_w$ is fixed to some *a–priori* (constant) estimate. In this paper an on–line wind speed estimator is proposed to generate the desired speed.

III. Wind Speed Estimation Problem

To formulate the estimation problem the following assumptions are needed.

Assumption 1 The power coefficient is a *known*, smooth, function $C_p : [0, \lambda_M] \to \mathbb{R}_+$, which verifies (3) and

$$C_p'(\lambda)\begin{cases} > 0 & \text{for} \quad \lambda \in [0, \lambda^\star) \\ = 0 & \text{for} \quad \lambda = \lambda^\star \\ < 0 & \text{for} \quad \lambda \in (\lambda^\star, \lambda_M], \end{cases} \tag{9}$$

where $(\cdot)'$ denotes differentiation.

Assumption 2 The wind speed v_w is an *unknown* positive constant.

Assumption 3 The electrical torque T_e and the motor speed w_m are *measurable*.

Problem Formulation Given the system (4) and (6), verifying Assumptions 1–3, design an on–line estimate of the wind speed, $\hat{v}_w$, such that, under some suitable conditions,

$$\lim_{t\to\infty} \hat{v}_w(t) = v_w.$$

That is, ensure that the parameter estimator is asymptotically consistent.

Some remarks regarding the assumptions are in order.

(R1) Concerning Assumption 1, as indicated above, the shape of $C_p(\lambda)$ can be easily obtained from experimental data. Furthermore, the conditions imposed on its derivative are consistent with the physical operation of the windmill. Namely, that power increases with the blade's tip speed up to a maximum point,

$$C_p^\star := C_p(\lambda^\star),$$

after which it starts decreasing. From the analytical viewpoint, this is a critical assumption that ensures some *monotonicity* conditions for $C_p(\lambda)$—needed for a proper behavior of the estimator.

(R2) The assumption of constant wind speed may seem stringent, particularly for its application in maximum power point tracking controllers. However, we propose an *on–line* estimator that, as is well–known [9], is able to track slowly–varying parameters. The time scale separation between the wind dynamics and the mechanical and electrical signals of the windmill systems is an additional argument to justify the assumption.

(R3) Regarding Assumption 3, measuring w_m is standard practice in windmill systems. Moreover, knowledge of T_e is available in permanent magnet synchronous or doubly–fed induction generators, which are the machines typically used in this application. Indeed, for the former, T_e is given by

$$T_e = \frac{3}{2}\frac{P}{2}\phi i_q. \tag{10}$$

where i_q is the current in the dq reference frame, ϕ is the permanent magnetic flux produced by the rotor magnets, and P is the number of pole pairs. For doubly–fed induction generators the torque is defined as

$$T_e = L_{sr}(i_{sq}i_{rd} - i_{sd}i_{rq})$$

with L_{sr} the mutual inductance and $(i_{sd}, i_{sq}), (i_{rd}, i_{rq})$ are, respectively, the stator and rotor currents—which are measurable in winded–rotor machines.

IV. Main Result

As can be seen from (4) and (6), wind speed enters into the system in a highly nonlinear way. Moreover, since the basic objective of the control is to track the maximum power point in the face of (slowly) varying wind speeds, the motor speed—and, consequently, λ—will take values in wide ranges, stymieing the application of standard linear estimation techniques for the linearized system.

A. Immersion and Invariance Parameter Estimators

In [7], [8] a new framework to design parameter estimators and adaptive controllers for nonlinearly parameterized nonlinear systems has been proposed. The key step is the construction of a monotone mapping, which explicitly depends on some of the estimator tuning parameters. The construction relies on the use of the immersion and invariance (I&I) ideas introduced in [2] for the design of adaptive stabilizing controllers and observers. See [1] for a recent overview of the applications of I&I.

The I&I identification technique of [8] is applied here to solve the wind estimation problem. A slight variation of the main result of [8]—suitable for our objective—is given below. The interested reader is referred to this reference for the proof of the proposition, and to [7], for further details and extensions of the result.

Proposition 1 Consider the system

$$\dot{x} = F(t) + \Phi(x, \theta), \tag{11}$$

where $x \in \mathbb{R}$, the function $F(t)$ and the mapping $\Phi : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ are known, and $\theta \in \mathbb{R}$ is a constant *unknown parameter*. Assume there exists a smooth mapping $\beta : \mathbb{R} \to \mathbb{R}$ such that the parameterized mapping

$$\begin{aligned} \mathcal{Q}_x &: \mathbb{R} \to \mathbb{R} \\ \mathcal{Q}_x(\theta) &:= \beta'(x)\Phi(x, \theta) \end{aligned} \tag{12}$$

is *strictly* monotone increasing,[3] where $\beta'(\cdot)$ denotes differentiation. The I&I estimator

$$\begin{aligned} \dot{\hat{\theta}}^I &= -\beta'(x)\left[F(t) + \Phi(x, \hat{\theta}^I + \beta(x))\right] \\ \hat{\theta} &= \hat{\theta}^I + \beta(x), \end{aligned} \tag{13}$$

is asymptotically consistent. That is,

$$\lim_{t\to\infty} \hat{\theta}(t) = \theta. \tag{14}$$

for all $(x(0), \hat{\theta}^I(0)) \in \mathbb{R} \times \mathbb{R}$, and $F(t)$ such that $(x(t), \hat{\theta}(t))$ exist for all $t \geq 0$.

Notice that Assumption 2 of Proposition 1 in [8] is conspicuous by its absence in the proposition above. This stems from the fact that, for the scalar parameter case, this Assumption is implied by the *strict* monotonicity condition.

[3] That is, for all $a, b \in \mathbb{R},\ a > b$, and all $x \in \mathbb{R}$, the mapping satisfies $\mathcal{Q}_x(a) > \mathcal{Q}_x(b)$.

B. Verifying the Monotonicity Condition

We will apply Proposition 1 to the system (4), (6) with v_w the unknown parameter, $x = \omega_m$ and

$$F(t) = -\frac{1}{J}T_e(t), \tag{15}$$

where T_e is viewed as a function of time. The key step is to construct a function $\beta(\cdot)$, such that the parameterized function

$$\begin{aligned} \mathcal{Q}_{\omega_m} &: \mathbb{R}_+ \to \mathbb{R} \\ \mathcal{Q}_{\omega_m}(v_w) &= \beta'(\omega_m)\Phi(\omega_m, v_w) \end{aligned}$$

is strictly monotonically increasing. In this scalar case, the latter is true if and only if the derivative of the function is positive, which is computed as

$$\begin{aligned} \mathcal{Q}'_{\omega_m}(v_w) &= \beta'(\omega_m)\frac{\partial \Phi(\omega_m, v_w)}{\partial v_w} \\ &= \frac{\rho A r}{2J} v_w \beta'(\omega_m)\left[\frac{3v_w}{r\omega_m}C_p\left(\frac{r\omega_m}{v_w}\right) - C'_p\left(\frac{r\omega_m}{v_w}\right)\right]. \end{aligned}$$

Obviously, since v_w is a positive constant, the monotonicity of $\mathcal{Q}_{\omega_m}(v_w)$ is determined by the product of the sign of $\beta'(\omega_m)$ and the sign of the term in brackets, which we write in the more convenient form

$$\kappa(\lambda) := \frac{3}{\lambda}C_p(\lambda) - C'_p(\lambda). \tag{16}$$

Now, since $\beta(\omega_m)$ is used in the construction of the estimator (13), it is clear that it cannot depend on the unknown v_w. Consequently, the monotonicity of $\mathcal{Q}_{\omega_m}(v_w)$ is (essentially) determined by $\kappa(\lambda)$. See Fig. 2 for one possible scenario.

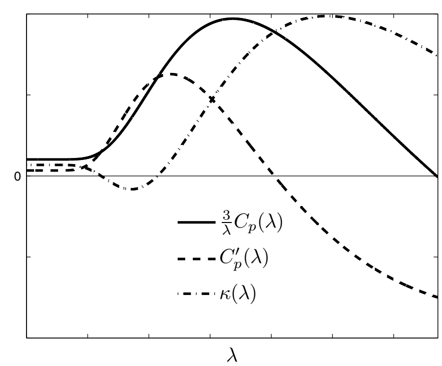

Fig. 2. Plots of $\frac{3}{\lambda}C_p(\lambda)$, $-C'_p(\lambda)$ and $\kappa(\lambda)$, for the case when $\kappa(\lambda)$ changes sign.

The lemma below plays a central role in our developments.

Lemma 1 Consider the function $\kappa(\cdot)$ defined by (16), with $C_p(\cdot)$ satisfying Assumption 1. There exists two constants, λ_{c1}, λ_{c2}, with

$$0 < \lambda_{c1} \leq \lambda_{c2} < \lambda^\star,$$

such that

$$\kappa(\lambda) > 0 \quad \text{for} \quad \lambda \in [0, \lambda_{c1}) \cup (\lambda_{c2}, \lambda_M].$$

Proof First, note that

$$\lim_{\lambda \to 0} \kappa(\lambda) = 2C'_p(0) > 0,$$

which follows from Assumption 1 and direct application of L'Hopital's Lemma to (16). Invoking continuity establishes the existence of $\lambda_{c1} > 0$ such that $k(\lambda) > 0$ for all $\lambda \in [0, \lambda_{c1})$. See Fig. 2.

Let us prove now the existence of $\lambda_{c2} < \lambda^\star$ such that $k(\lambda) > 0$ for all $\lambda \in (\lambda_{c2}, \lambda_M]$. First, from the facts that $C'_p(\lambda) \leq 0$ for all $\lambda \geq \lambda^\star$, and $\frac{3}{\lambda} C_p(\lambda) > 0$ for all λ, we conclude that $k(\lambda) > 0$ for all $\lambda \in [\lambda^\star, \lambda_M]$. Now, again from continuity and the fact that $C'_p(\lambda^\star) = 0$ we conclude that there exists $\lambda_{c2} < \lambda^\star$ such that $k(\lambda) > 0$ for all $\lambda \in (\lambda_{c2}, \lambda^\star]$. Putting both arguments together proves the claim.

Now, assume there is no zero crossing of $\kappa(\lambda)$. Then, we can set $\lambda_{c1} = \lambda_{c2}$ to be any constant in the interval $(0, \lambda_M)$. In that case, $\kappa(\lambda) > 0$ for all $\lambda \in [0, \lambda_M]$. On the other hand, if there is a zero crossing—obviously, in the interval $(0, \lambda^\star)$—there are necessarily (at least) two of them, because $k(0), k(\lambda_M) > 0$. Selecting λ_{c1} and λ_{c2} to be, respectively, the smallest and largest of these roots establishes that $\lambda_{c1} < \lambda_{c2}$, completing the proof. □□□

We now recall that our interest is to study the monotonicity of the function $\mathcal{Q}_{\omega_m}(v_w)$. In particular, we want to define intervals for ω_m where the function is increasing, which is an immediate corollary of Lemma 1, (2), and Assumption 1.

Corollary 1 Fix $\beta(\omega_m)$ such that sign $\beta'(\omega_m) > 0$. The function $\mathcal{Q}_{\omega_m}(v_w)$ verifies either one of the following properties.

- P1 $\mathcal{Q}_{\omega_m}(v_w)$ is monotonically increasing for all ω_m.
- P2 There exists $\omega_m^{c2} < \omega_m^*$ such that $\mathcal{Q}_{\omega_m}(v_w)$ is monotonically increasing for all $\omega_m > \omega_m^{c2}$—where $\omega_m^\star$ is defined in (7) and ω_m^{c2} is defined via (2) with λ_{c2} .

C. I&I Estimator

We are in position to present the main result of the paper.

Proposition 2 Consider the system (4), (6), verifying Assumptions 0–3. The I&I estimator

$$\begin{aligned} \dot{\hat{v}}_w^I &= \gamma[\frac{1}{J} T_e - \Phi(\omega_m, \hat{v}_w^I + \gamma \omega_m)] \\ \hat{v}_w &= \hat{v}_w^I + \gamma \omega_m, \end{aligned} \tag{17}$$

where $\gamma > 0$ is an adaptation gain, is asymptotically consistent, that is,

$$\lim_{t \to \infty} \hat{v}_w(t) = v_w$$

if either one of the conditions below holds.

C1 The power coefficient verifies

$$\frac{3}{\lambda} C_p(\lambda) > C'_p(\lambda), \tag{18}$$

for all $\lambda \in (0, \lambda^\star)$.

C2 The generator speed remains in the range

$$\omega_m(t) > \omega_m^{c2} \tag{19}$$

for all $t \geq 0$, where ω_m^{c2} is defined in Corollary 1.

Proof. Set

$$\beta(\omega_m) = \gamma \omega_m. \tag{20}$$

From Corollary 1 we conclude that, if condition C1 is satisfied, the function $\mathcal{Q}_{\omega_m}(v_w)$ is monotone for all ω_m. On the other hand, if condition C2 holds, it is monotone for $\omega_m > \omega_m^{c2}$. The proof is completed invoking Proposition 1 and replacing (15) and (20) in (13) to get (17). □□□

V. PI Control and Simulation Results

In this section we assess, via computer simulations, the performance of the wind speed estimator, a fixed controller and a certainty equivalent adaptive controller. We adopt the simplified—but widely adopted, see *e.g.*, [3], [4] and references therein—scenario that neglects the dynamics of the generator and its power converter, and assumes that the electrical torque T_e is actually a control variable, for which a standard PI controller around the rotor speed error is proposed. That is,

$$\begin{aligned} T_e &= K_P(\omega_m - \omega_m^d) + K_I \xi \\ \dot{\xi} &= (\omega_m - \omega_m^d), \end{aligned} \tag{21}$$

where $K_P, K_I > 0$ are tuning gains and $\omega_m^d > 0$ is, either fixed to a constant value for the nonadaptive PI controller via (8), or adjusted on–line using the estimated wind speed (17), for its adaptive version.

A. Stability Analysis of the Fixed PI Control

The nonadaptive PI enjoys the following stability properties.

Proposition 3 Consider the system (4), (6), verifying Assumptions 0–3 in closed–loop with the PI controller (21).

(i) The system has a unique equilibrium point

$$\{\omega_m = \omega_m^d, \xi = \frac{J}{K_I} \Phi(\omega_m^d, v_w)\}.$$

(ii) All trajectories are bounded and the system is ultimately bounded. That is, there exists time $t_c > 0$, such that

$$\begin{aligned} |\omega_m(t) - \omega_m^d| &\leq \frac{1}{K_P} \kappa \\ |\xi(t) - \frac{J}{K_I} \Phi(\omega_m^d, v_w)| &\leq \frac{1}{2K_I} \kappa, \end{aligned}$$

for all $t \geq t_c$, where

$$\kappa := \frac{\rho A v_w^3}{\omega_m^{\min}} C_p(\frac{r \omega_m^\star}{v_w}).$$

(iii) There exists $K_P^{\min} > 0$ such that, for all $K_P \geq K_P^{\min}$ the equilibrium is asymptotically stable.

Proof. Claim (i) follows immediately from inspection of (4), (6), (21).

To prove (ii) define the error signals

$$\begin{aligned} \tilde{\omega}_m &:= \omega_m - \omega_m^d \\ \tilde{\xi} &:= \xi - \frac{J}{K_I} \Phi(\omega_m^d, v_w) \end{aligned}$$

and consider the positive definite function

$$V(\tilde{\omega}_m, \tilde{\xi}) := \frac{1}{2}\tilde{\omega}_m^2 + \frac{K_I}{J}\tilde{\omega}_m\tilde{\xi} + \frac{1}{J}(K_I + \frac{K_P^2}{2J})\tilde{\xi}^2,$$

whose derivative, along the solutions of (4), (6), (21), verifies

$$\begin{aligned}\dot{V} &= -\frac{K_P}{2J}\tilde{\omega}_m^2 - \frac{K_P K_I}{2J^2}\tilde{\xi}^2 + \\ &+ (\tilde{\omega}_m + \frac{K_P}{2J}\tilde{\xi})[\Phi(\omega_m, v_w) - \Phi(\omega_m^d, v_w)] \\ &\leq -\frac{K_P}{2J}|\tilde{\omega}_m|[|\tilde{\omega}_m| - \frac{1}{K_P}\kappa] - \frac{K_P K_I}{2J^2}|\tilde{\xi}|[|\tilde{\xi}| - \frac{1}{2K_I}\kappa]\end{aligned}$$

where—to get the bound—we have used (6) and the fact that

$$\Phi(\omega_m, v_w) - \Phi(\omega_m^d, v_w) \leq \frac{\kappa}{2J},$$

see Fig. 1. This establishes the claim.

Now, the linearization of the closed–loop system at the equilibrium point yields the system matrix

$$\begin{bmatrix} -\frac{K_P}{J} + \frac{\partial \Phi}{\partial \omega_m}(\omega_m^d, v_w) & -\frac{K_I}{J} \\ 1 & 0 \end{bmatrix}.$$

which is Hurwitz for sufficiently large K_P, establishing the claim. □□□

B. Simulation Results

The performance of the system is tested simulating step changes in the wind speed. The gains of the PI were selected using pole placement techniques after linearizing the system around the initial operating point, which is taken to be the one of maximum power extraction. The parameter γ, which essentially determines the speed of convergence of the estimator, was selected via trial–and–error. All simulations are executed using the Matlab–Simulink ® software package.

As is customary, for the purposes of the simulation we assume the power coefficient is given by the function

$$C_p(\lambda) = e^{-\frac{c_{p1}}{\lambda}}\left(\frac{c_{p2}}{\lambda} - c_{p3}\right) + c_{p4}\lambda, \qquad (22)$$

where the coefficients $c_{pi}, i = 1, \ldots, 4$—that are windmill–specific, but independent of v_w and ω_m—are known. These coefficients were taken from the benchmark problem of [12], and have the following values: $c_{p1} = 21$, $c_{p2} = 125.21$, $c_{p3} = 9.8$, and $c_{p4} = 0.0068$. This yields $\lambda_* = 8.1$ and

$$C_p^\star := C_p(\lambda^\star) = 0.48.$$

The resulting function $C_p(\lambda)$ verifies the key inequality (18), hence global convergence of the estimator is ensured.

Figure 3 shows the response of the error between the optimal and the actual speed for the nonadaptive PI controller. The reference speed, ω_m^d, was fixed assuming the wind is known at $t = 0$. The initial condition of the speed was also selected corresponding to its optimal value, and the integrator was initialized at zero, i.e., $\omega_m(0) = \omega_m^\star(0)$ and $\xi(0) = 0$, respectively. As shown in the figure, when the wind speed changes $\omega_m^d \neq \omega_m^*$ and the rotor speed that, as predicted by Proposition 3, converges to ω_m^d, moves away from its optimal value of maximum power extraction. The global behavior of the adaptive PI controller is illustrated in Fig 4, where —for a fixed set of PI and estimation gains— several trajectories starting on a disk at $\xi(0) = 0$ are shown to converge to a unique equilibrium point.

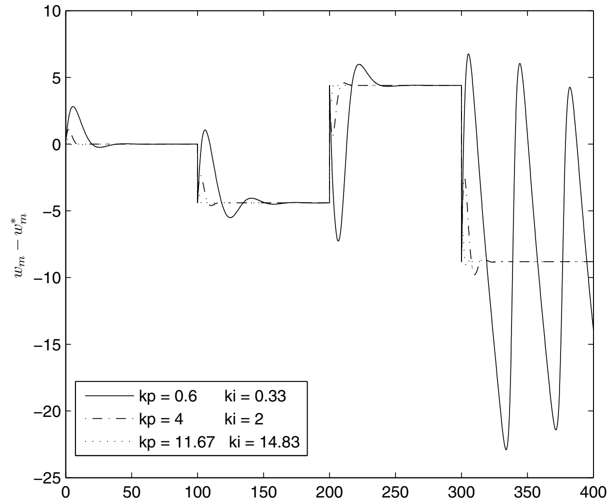

Fig. 3. Performance of the nonadaptive PI, speed deviations with respect to the optimal values for different PI gains.

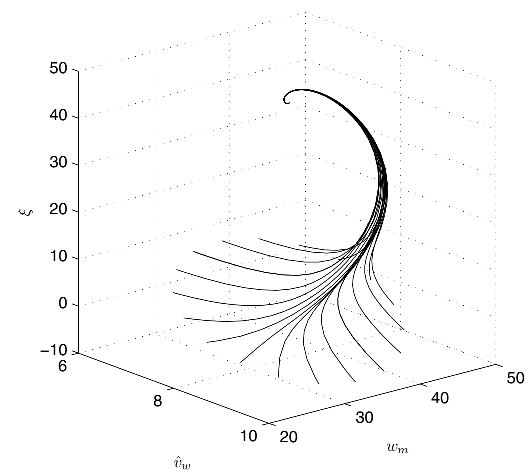

Fig. 4. Behavior of the adaptive PI, with $K_P = 0.59$, $K_I = 0.32$ and initial conditions on a disk at the plane $\xi(0) = 0$.

The performance of the certainty equivalent adaptive PI controller is shown in Fig. 5, where we have set $\hat{v}_w(0) = v_w(0)$, and the same initial conditions for the speed and integral action as for the nonadaptive case. As may be observed, the system behaves as desired, with the power coefficient matching its optimal value, and hence maximum power is being (asymptotically) extracted for all wind speeds.

VI. Conclusions and Future Research

An estimator for the wind speed of a windmill system, with guaranteed convergence properties, has been presented.

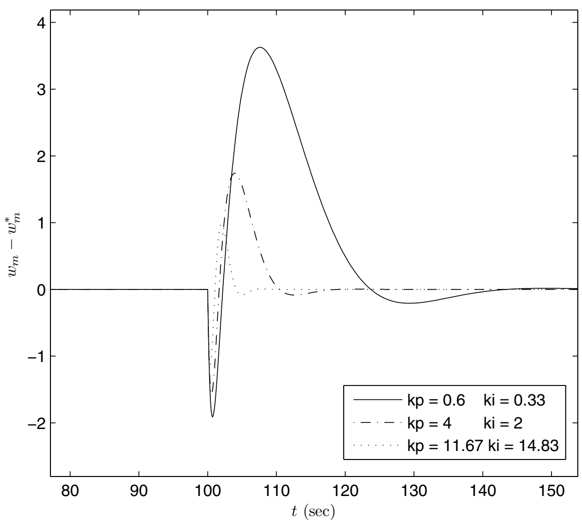

Fig. 5. Performance of the adaptive PI, speed deviations with respect to the optimal values for different PI gains.

The result is global if the power coefficient verifies (18). This condition can be easily checked numerically. Unfortunately, if (18) does not hold, we have to rely on the signal–dependent assumption (19), which cannot be verified *a–priori*. Indeed, there is no way to guarantee that in closed–loop operation the speed $\omega_m(t)$ will remain above the value ω_m^{c2}, which is furthermore not known. However, the proposition guarantees that there is an interval, containing $\omega_m^\star$, where the speed estimation will "go in the right direction". Given the complexity of the problem, we tend to believe that this kind of local results are the best one can hope for without further assumptions on $C_p(\lambda)$. It should be underscored that the simulation results presented in Section V confirm the good behavior of the proposed estimator.

From Proposition 2 it is known that the estimation error decreases when $\mathcal{Q}_{\omega_m}(v_w)$ is increasing. It can also be shown [8], that the error will *increase* if $\mathcal{Q}_{\omega_m}(v_w)$ is decreasing.[4] In other words, if (18) does not hold, the estimator will not behave correctly only in a finite interval of motor speeds, but will tend to converge to the true value outside this interval.[5] Interestingly, the "good" intervals include the low and high speed ranges, as well as the optimal speed. Unfortunately, this information is not enough to predict the global behavior of the system—hence the need for assumptions (18) or (19).

Current research is under way to explore the possibility of introducing, in the spirit of [11], a reparametrization of the wind speed to relax the conditions (18) or (19). Also, to improve the performance of the overall system, we are investigating the use of other, possibly nonlinear, controllers to replace the PI reported here. For instance, for stand–alone applications, in [10] the PI controller is replaced by an nonlinear passivity–based controller designed taking into account the dynamics of the generator and the power converter. Currently, we are investigating windmill systems connected to the network. The results of these researches will be reported in the near future.

[4]Changing the sign of γ would correct the problem. Alas, these intervals are not known.

[5]Typically, there are only two positive roots of $\kappa(\lambda)$, hence only one "bad" interval. But the possibility of having more than one cannot be ruled out without further assumptions on $C_p(\lambda)$.

Acknowledgements

F. Mancilla-David acknowledges the University of Colorado Denver and the "Centre National de la Recherche Scientifique" of France for supporting this research. The work of F. Jaramillo has been supported by CONACyT, Mexico and the French Embassy in Mexico.

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