2013 European Control Conference (ECC)
July 17-19, 2013, Zürich, Switzerland.

Observer-based maximum power tracking in wind turbines with only generator speed measurement*

John Sandoval-Moreno, Gildas Besançon and John J. Martinez

***Abstract*— In this paper, it is proposed a technique to optimize the power generated by a small scale wind turbine, by having *no wind speed measurement and uncertain knowledge of the power coefficient curve characteristic*. First, a Kalman-like observer is used for estimating the power coefficient characteristic, which is then used in a nonlinear control strategy for the electrical generator that secures power maximization. Then, the uncertain power coefficient function is adjusted with a Recursive Least-Square algorithm that uses the estimate of the power coefficient as reliable information. Finally, from the adjusted power coefficient polynomial is computed the optimal electrical generator speed reference that leads the system to operate near the theoretical optimal power. This methodology is illustrated on a simulated example and compared with a case when the wind speed is measured.**

Keywords: Wind power systems; Power generation; Linearizing control; Nonlinear estimation.

I. Introduction

In the last decades, the obtention of electric energy from alternative sources has motivated the development of various technologies, which include fuel cells, photovoltaic panels, wind turbines, among others. In particular, *electric wind power generators* (EWPGs) have become one of the alternative power sources with a remarkable growing in installed capacity and electric energy generation, considering onshore and offshore wind turbines, in nations such as Denmark, United Kingdom, United States, Germany, Spain and China [1]. However, EWPGs - as well as the other power generation technologies, should operate with adequate control strategies that not only permit the secure operation of the system, but also ensure their optimal operative conditions, that is to deliver the maximum amount of power from actual wind conditions.

In practice, optimal power generation for the EWPGs can be obtained by using some adequate knowledge of the *wind turbine power coefficient* (known as C_P), which relates the efficiency of the wind turbine to the wind speed [2], [3], [4]. One of the most exploited control strategy which is then applied - not only in EWPG, but also in photovoltaic generation systems [5] - is the so-called *Maximum Power Point Tracking* (MPPT) strategy. This technique considers *a priori* knowledge of the power generation characteristics and tries to drive the system to the optimal operation condition via small changes in the control system reference signals. This technique, although robust and reliable, could have some troubles in its implementation with possible chattering of the power generated by the convergence around the optimal operation point, or even with the online computation of gradients and nonlinear estimations. However, those restrictions can be overcome with some precautions. Other control strategies, also related with the C_P function, assume the knowledge of its maximum power point and regulate the system around it. Classical PID controllers, as well as robust and nonlinear control strategies (see eg [4], or more recently [6]) with the support of look-up tables or even MPPT auxiliary algorithms have given rise to reliable solutions to the power generation control. Nevertheless, they all require the knowledge of the exact value of the maximum wind turbine efficiency, which is not available if the C_P curve parameters are pretty uncertain. To overcome this inconvenient, some authors have considered the online estimation of the power coefficient. The determination of the EWPG mathematical model and the use of state observers for parametric estimation, with the support of measurements from the power system (torques, speeds, currents, voltages), allow to obtain the current value of the C_P parameter [7] or the polynomial that describes this function [8]. Nevertheless, the proposed techniques requires the wind speed knowledge, by means of anemometers, look-up tables or observers [9],[10] that could also require information on the power coefficient. This strong interdependence between wind speed and power coefficient will affect the control loop, making it difficult to find the optimal references for the system. In addition, the wind speed measurement has some drawbacks related with delays, sensors location and noises in the measurement, affecting its quality.

In view of those practical inconvenients, the present paper proposes an alternative method to obtain optimal power generation for an EWPG *without measurement of the wind speed and with uncertain knowledge of the C_P parameters*. The solution includes an estimation of some power characteristic of the wind turbine, as well as the online correction of the C_P curve parameters, from which an optimal reference signal for the generator speed is continuously obtained, which finally guarantees the maximum power extraction from the turbine (as in MPPT approaches).

The paper is organized as follows: Section II recalls the main concepts and models for EWPG systems, and section III presents the proposed control algorithm for optimal power generation. Section IV then gives some simulation results,

*This work was in part supported by the "Francisco José de Caldas" Institute for the Development of Science and Technology (COLCIENCIAS) grant from Colombia (J.Sandoval), and also by French ANR - Project WINPOWER

GIPSA-Lab, Control Systems Department, Grenoble Institue of Technology, Ense[3], BP 46, 38402 Saint-Martin d'Hères, France. {john-anderson.sandoval-moreno,john.martinez, gildas.besancon}@gipsa-lab.grenoble-inp.fr

∘ G. Besançon is also with Institut Universitaire de France.

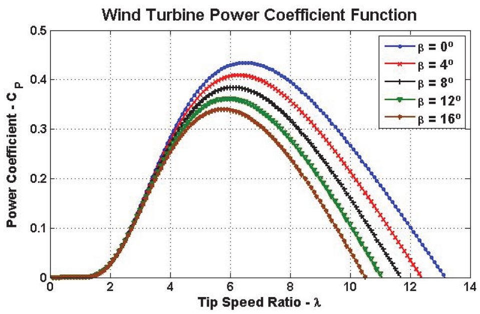

Fig. 1. Typical wind turbine power coefficient for different pitch angles

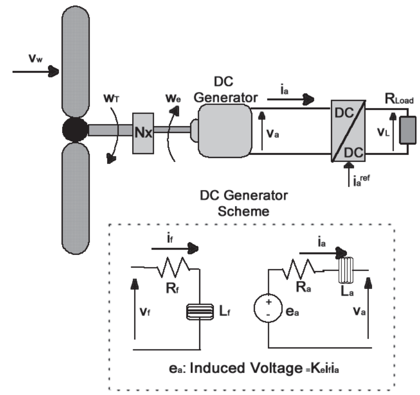

Fig. 2. Scheme of the considered wind power generation system.

and conclusions will be found at the end of the paper.

II. Electric Wind Power Generation system

A. Power generation in EWPG

For wind turbines, there are well known expressions that can be applied to compute the power generated in the turbine P_T, according to the wind speed v_w and the power coefficient C_P as in (1) below, where ρ is the air density and R the wind turbine radius:

$$P_T = \frac{1}{2}\rho\pi R^2 C_P(\lambda,\beta)v_w^3 \tag{1}$$

The power coefficient C_P is a parameter that relates the amount of power transmitted to the turbine shaft from the power provided by the wind. It is function of the turbine pitch angle β and a parameter λ, known as the Tip Speed Ratio (TSR), expressed in (2), where w_T is the turbine shaft angular speed. The C_P function can be written in the form (3) for β constant, and can be represented graphically as shown in Fig 1. (see eg [3] and [2]).

$$\lambda = \frac{w_T}{v_w}R \tag{2}$$

$$C_P(\lambda) = \sum_{i=0}^{n_\lambda}\alpha_{ij}\lambda^i \tag{3}$$

According to the C_P descriptions above, it is possible to obtain an optimal power coefficient value in function of λ for a fixed value of β. Operating the system at this value then provides the maximum of energy from the wind.

The problem is then to design a corresponding control, and a challenge is to do it without speed measurement, nor accurate knowledge of the parameters in the C_p function (3).

In the present paper, a solution is proposed under the assumption of constant pitch angle β, and assuming an operation without any saturation in a so-called *Partial Load Region* (see [4], [11], [12], [13]).

B. Mathematical modelling of EWPG

The wind power generation system configuration that is used in this work is presented in Fig 2. The scheme includes the wind turbine and its mechanical coupling system with the shaft of a DC separately excited electrical generator. The armature winding is coupled with a DC/DC power converter for the regulation of the generated power and delivers it to an electrical load, which is typically a DC/AC conversion system for grid integration [14] or stand alone applications [15]. However, the present paper is devoted to optimal power generation, and the problem of grid connection is left for further studies.

The considered EWPG can then be described by differential equations that relate electrical dynamics (see (4)-(5) below) to the mechanical ones (see (6)-(8)).

In the electrical equations, U, i, L, R respectively denote voltage, current, inductance and resistance variables, with index f or a respectively for field and armature, and K_e is the induced EFM constant.

For the mechanical equations, J_{eq} is the equivalent inertia (referred to the generator shaft), B_e is the friction constant of the generator and w_e its angular speed. In addition C_p is the power coefficient, and $K_T = 0.5\pi\rho N_x R^2$, with ρ the air density (in kg/m^3), R the wind turbine radius (in m), and N_x the speed ratio, fixed by the gearbox. Finally, v_w denotes the wind speed, assumed to vary around a mean value V_{w0} with a bandwidth represented by α_v, and stochastic fluctuations described by η_v (zero mean white noise).

$$\dot{i_f} = \frac{U_f}{L_f} - \frac{R_f}{L_f}i_f \tag{4}$$

$$\dot{i_a} = \frac{K_e i_f}{L_a}w_e - \frac{R_a}{L_a}i_a - \frac{U_a}{L_a} \tag{5}$$

$$\dot{w_e} = \frac{K_T C_p {v_w}^3}{J_{eq}w_e} - \frac{B_e}{J_{eq}}w_e - \frac{K_e i_f}{J_{eq}}i_a \tag{6}$$

$$v_w = V_{w0} + \tilde{v_w} \tag{7}$$

$$\dot{\tilde{v_w}} = -\alpha_v\tilde{v}_w + \eta_v \tag{8}$$

It should be noticed that α_v actually represents the frequency range of wind speed components that generates a significant amount of energy. In practice, the turbine usually generates rotational energy for low frequency wind speed components. This constant α_v is then defined from the turbine model (response vs wind variations) or even from the wind speed spectral response. In [4], one can find some characterization of eolian energy behaviors and its effective

TABLE I

6-KW WIND GENERATOR PARAMETERS

Parameters	Value
Turbine Radio, R	4.0 m
Turbine inertia, J_T	1.5 kgm^2
Wind speed range	$2-12\ ms^{-1}$
Transmission ratio, N_x	7.5
Wind density, ρ	1.25 kgm^{-3}
DC generator inertia, J_e	0.3 kgm^2
Maximum DC generator output power, P_{gen}	6.0 kW
Rated field voltage, V_f	120 V
Rated armature voltage, V_a	240 V
Rated field flow, ϕ_f	0.12 Wb
Rated field current flow, I_F	2 A
Field inductance, L_f	60 mH
Field resistance, R_f	60 Ω
Armature inductance, L_a	10 mH
Armature resistance, R_a	2.0Ω
Friction constant, B_e	0.015
Induced EFM constant, K_e	0.5
Wind speed time constant, α_v	0.2
Theoretical $\alpha_{i=0\ldots8}$'s for the C_p polynomial $C_P(\lambda)=\sum_{i=0}^{8}\alpha_i\lambda^i$ [0.002897 0.001346 -0.03324 0.03313 -0.008475 0.00101 $-6.345x10^{-5}$ $2.031x10^{-6}$ $-2.621x10^{-8}$]	

bandwidth, which depends on the wind speed mean value, but can be considered between 0.05 and 0.8 rad/s for the operative wind speed range for the turbines.

For a concrete example of actual values for all the considered parameters, Table I gives a realistic list corresponding to a $6-kW$ wind generator, which will be used for the simulations in this paper.

Finally, for the proposed control strategy, only the mechanical equation will be used, assuming that only the generator speed w_e is known, together with the constant parameters and the driving currents i_f, i_a. In practice, the armature current reference i_a^{ref} is given to the current control loop of the DC/DC converter (typically a Boost converter), that acts directly to the duty cicle variations [16]. This additional control strategy will be considered in further works, in which the grid interaction will be evaluated In particular, the coefficients in the C_p function as well as the wind velocity (both v_w and V_{w0}) will be considered to be unknown.

III. PROPOSED CONTROL STRATEGY FOR EWPG

A. Reduced model for control design

For the purpose of control design for maximum power tracking, let us assume that the generator field current i_f is constant, and the armature current i_a is used to regulate the generator speed (see eg [17]).

Model (4)-(6) can then be reduced to equation (6) where $i_a = u$ is the control variable, and $y = w_e$ is the measured variable.

If the electrical generator is based in other technology (for example *Permanent Magnets Synchonous Generators - PMSG* [15]), the mechanical equation (see (6)) is still valid. The control strategy will deliver an optimal control signal u, proportional to the electrical torque, that should secure the optimal operation of the power system for extracting the maximum power, according to the optimization algorithm. This approach will be analyzed in future works.

In addition, this control model can be even more simplified by assuming that $C_P \simeq C_{P0}$ constant (ie $\dot{C}_{P0} = 0$), equivalent to consider slow variations of C_P compared with the wind speed variations.

By setting then $z := C_p v_w^3$ as a new variable, and $K_1 := K_T/J_{eq},\ K_2 := B_e/J_{eq},\ K_3 := K_e i_f/J_{eq}$ as new known constants, equations (6)-(8) become:

$$\dot{w_e} = \frac{K_1 z}{w_e} - K_2 w_e - K_3 u \tag{9}$$

$$\dot{z} = -3\alpha_v z + 3\alpha_v C_{P0} V_{w0} v_w^2 + \eta_z \tag{10}$$

for some η_z resulting from definition of z and η_v in equation (8). In this model, α_v is assumed to be established according to the effective wind bandwidth that affects the turbine (if nothing is known about it, it could be used as a tuning parameter).

In view of equation (9), the velocity w_e can directly be controlled by an exactly linearizing feedback [18], provided that z is known. This suggests the use of an observer.

B. State estimation

Based on representation (9)-(10) and $y = w_e$, the model can be transformed in order to be able to design a Kalman observer, following a procedure similar to that of [19], [20] for instance. Define indeed new variables as follows: $z_1 = w_e$, $z_2 = z$, $z_3 = 3\alpha_v C_{P0} V_{w0} v_w^2$, $z_4 = 6{\alpha_v}^2 C_{P0} V_{w0}^2 v_w$ and $z_5 = 6{\alpha_v}^3 C_{P0} V_{w0}^3$.

Then the model becomes:

$$\dot{z}(t) = A(z(t))z(t) + Bu(t) + \eta_{z_{obs}}$$

$$\dot{z}(t) = \begin{bmatrix} -K_2 & \frac{K_1}{z_1} & 0 & 0 & 0 \\ 0 & -3\alpha_v & 1 & 0 & 0 \\ 0 & 0 & -2\alpha_v & 1 & 0 \\ 0 & 0 & 0 & -\alpha_v & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} z(t) + \begin{bmatrix} -K_3 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} u(t) + \begin{bmatrix} 0 \\ \eta_z \\ \eta_{z_3} \\ \eta_{z_4} \\ 0 \end{bmatrix} \tag{11}$$

$$y(t) = Cz(t)$$

$$y(t) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix} z(t)$$

where the η_{z_i}'s are noise terms resulting from η_z and the transformation.

Noting that z_1 entering in the state matrix above is measured, and can thus be injected in the observer, the system takes the form of time-varying linear one, for which a Kalman-like observer can be designed [21].

Assuming discrete-time measurements, a discretized version

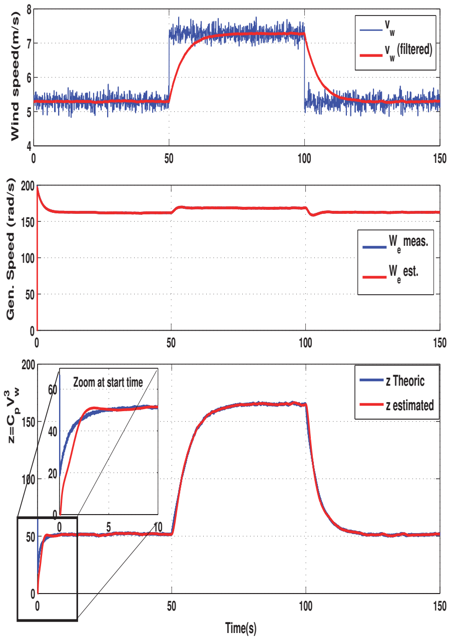

Fig. 3. Performance of the state estimator for w_e, z under noisy wind (top)

of the above model can be considered, for which a classical Kalman observer can be designed as follows (see eg [22]):

$$\begin{array}{rcl} P_{k|k} & = & A_k P_{k|k-1} A_k^T + Q_k \\ K_k & = & P_{k|k} C^T \left(C P_{k|k} C^T + R \right)^{-1} \\ \hat{z}_{k+1|k} & = & A_k \hat{z}_{k|k} + B_k u_k + K_k \left(y_k - C \hat{z}_{k|k} \right) \\ P_{k|k+1} & = & (I - K_k C) P_{k|k} \end{array} \quad (12)$$

where $A_k = (I + T_s A(z(kT_s)))$,$B_k = T_s B$, T_s denotes the sampling time, and Q_k, R_k are tuning matrices.
Simulation results with this observer and the system corresponding to table I are presented in Fig. 3. In those simulations, matrices P, Q and R are set to $1000I$, $0.5I$ and 5 respectively, and $T_s = 10ms$. Those values were selected according to the high untertainty on the estimated variables (high P values), the process noise (Q assigned according to the process noise) and the observer noise, in which R is selected higher than Q for noisy applications [22].
The figure presents the estimation of z, as well as the estimation of the generator speed. In this verification, a wind speed profile with a step variation and high noise was injected to the system, while a step variation in the armature current was made. The estimated z matches well the one obtained directly from the product $C_p(\lambda)v_w^3$, using a function of order eight in the simulated model.

C. Speed control strategy

With the estimation of z, it is possible to propose a control strategy that deals with the nonlinearity of our reduced model (9): considering indeed a control of the form $u = \frac{1}{K_3}(K_1 \hat{z}/w_e - K_2 w_e - u_{ext})$, the generator speed equation becomes that of a simple integrator $\dot{w}_e = u_{ext}$. It can thus be driven by a simple linear controller. Choosing a PI structure, some optimal LQ design can be used to obtain a good performance for reference tracking [23].
In this LQ design, the weights have been chosen as $Q_0 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$ and $R_0 = 2$, and the obtained state feedback gains are $K_p = 1.1892$ for the proportional one and $K_i = -0.7071$ for the integral one.

We are then left with the problem of choosing the speed reference for the purpose of maximum power tracking.

D. Optimal speed reference construction

For the purpose of optimal speed choice w.r.t. the power generation, let us first come back to the power coefficient C_P, and consider from now on a more precise model for it (even though still approximated) in the control strategy, of the form:

$$C_p(\lambda) = \alpha_0 + \alpha_1 \lambda + \alpha_2 \lambda^2 + \alpha_3 \lambda^3 \quad (13)$$

where coefficients α_i, $i = 0, 1, 2, 3$ are uncertainly known (typically, they are obtained for each condition of turbine pitch angle (see Fig. (1)), from practical tests which are affected by many factors).
Remember then that maximizing the power means maximizing C_P with respect to λ, and from our definition of z, this in turn results in maximizing z with respect to the generator speed w_e. The proposed solution is thus based on the online computation of the gradient coefficients of $\hat{z}$ with respect to w_e, and on the determination from them of the optimal reference value for w_e. Those coefficients are obtained from the on-line estimate of z (from the Kalman observer) on the one hand, and its expansion with respect to w_e from its definition $z = C_p(\lambda)v_w^3$ and (13) on the other hand:

$$\begin{array}{rcl} \hat{z} & = & C_p(\lambda) v_w^3 \\ \hat{z} & = & \left(\alpha_0 + \alpha_1 \lambda + \alpha_2 \lambda^2 + \alpha_3 \lambda^3 \right) v_w^3 \\ \hat{z} & = & \bar{\alpha}_0(t) + \bar{\alpha}_1(t) \omega_e + \bar{\alpha}_2(t) \omega_e^2 + \bar{\alpha}_3(t) \omega_e^3 \end{array} \quad (14)$$

where $\bar{\alpha}_0(t) = \alpha_0 v_w^3(t)$, $\bar{\alpha}_1(t) = \frac{\alpha_1 R}{N_x} v_w^2(t)$, $\bar{\alpha}_2(t) = \frac{\alpha_2 R^2}{N_x^2} v_w(t)$ and $\bar{\alpha}_3(t) = \frac{\alpha_3 R^3}{N_x^3}$, using $\lambda = \frac{R w_e}{N_x v_w}$ and the wind speed value V_{w0} for the instant $t = 0$.
This means that $\hat{z}$ can be re-written as:

$$\hat{z}_R = \theta^T \phi \quad (15)$$

with $\theta^T = [\bar{\alpha}_0(t)\ \bar{\alpha}_1(t)\ \bar{\alpha}_2(t)\ \bar{\alpha}_3(t)]$ and $\phi = [1\ \omega_e\ \omega_e^2\ \omega_e^3]^T$, and assuming variations of θ slow enough, a **Recursive Least Square algorithm - RLSA** can be used for its on-line adjustment, which will be called $\hat{\theta}$.
In the implementation, a forgetting factor $\zeta = 0.95$ is used, which ponderates the most recent information vs the older one [22]:

$$\begin{array}{rcl} \hat{z}_{Rk} & = & \hat{\theta}_{k-1}^T \phi_k \\ e_k & = & \hat{z}_{Rk} - \hat{z}_k \\ R_k & = & \zeta + \phi_k P_k \phi_k^T \\ P_{k+1} & = & \zeta^{-1} \left(P_k - P_k^{-1} \phi_k^T \phi_k P_k \right) \\ \hat{\theta}_k^T & = & \hat{\theta}_k^T - R_k^{-1} P_k e_k \phi_k \end{array} \quad (16)$$

where $\hat{z}_k$ is the estimate obtained for z by the previous observer, and $\hat{\theta}_k$ denotes the current estimate (adjusted by

the RLSA algorithm) for θ.
Notice that for this algorithm to converge, some pseudo-random binary signal (PRBS) is added to the control signal in order to guarantee that the algoritm always has information to compute the coefficients. For our case, the added signal has a variance of $0.1A^2$.
From those estimations, the gradient of z can finally be obtained as:

$$\widehat{\frac{\partial z}{\partial w_e}} = \hat{\hat{\alpha}}_1(t) + 2\hat{\hat{\alpha}}_2(t)\omega_e + 3\hat{\hat{\alpha}}_3(t)\omega_e^2 \quad (17)$$

where coefficients $\hat{\hat{\alpha}}_i$, $i = 0, 1, 2, 3$ are the coefficients of $\hat{\theta}$ from the RLSA algorithm. From (17), the optimal value for w_e can be deduced, as the one canceling the expression. To obtain this value, it can be used predefined routines that solves polynomial expressions such $roots$ in MATLAB's environment. In case of obtaining complex conjugate solutions, the use of the norm of each root is recommended.

IV. Simulation results

In this section will be shown and discussed the results of the simulations using Matlab version R2011b.

A. Validation of the proposed method

For the validation of the full above approach, the system described in Table I, was again used. In this case, the optimal couple (λ^*, C_p^*) is $(8.3, 0.4547)$, and for the maximum wind speed $12m/s$, a mechanical power of $6kW$ should be obtained.
In the simulations, the initial conditions of the system were computed for an electrical power of $1.5kW$, the posterior wind speed variations are steps of $1.2m/s$, after the initial value of $5.3m/s$ (V_{w0}), which is equivalent to a quiet wind of $18km/h$. With these wind speed range, the system will not operate at saturation conditions.
At the same time, it was considered that the wind speed is additionally subject to a noise of zero mean and variance equal to $0.025(m/s)^2$.
Finally, the values initially assumed for the 3rd order C_p polynomial model used in the control strategy are: $\alpha_0 = -0.4708, \alpha_1 = 0.2652, \alpha_2 - 0.02133, \alpha_3 = 4.69x10^{-4}$, from which the optimal couple (λ^*, C_{pt}^*) is $(7.5, 0.452)$, that is slightly different from the real one.
The proposed method was compared directly with the case in which the wind speed is measured. The idea is to estimate directly the C_p from the system, and this can be obtained by taking the z estimated and making $\hat{C}_p = \hat{z}/v_w^3$.
Then the $\alpha_i' s$ coefficients can be obtained from the RLSA, by considering:

$$\hat{C}_p = \theta_n^T \phi_n \quad (18)$$

with $\theta_n^T = [\alpha_0(t)\ \alpha_1(t)\ \alpha_2(t)\ \alpha_3(t)]$ and $\phi_n = [1\ \lambda\ \lambda^2\ \lambda^3]^T$ using $\lambda = \frac{Rw_e}{N_x v_w}$. Finally, the polynomial described in (14) can be obtained and the gradient polynomial-based control strategy can be used. In this case, the $\hat{C}_p$ polynomial will have fixed coefficients, and the wind speed measurement will affect directly the values of the gradient polynomial. Evidently, the optimal generator speed reference will be computed dynamically, as before.
In Fig. 4 are shown the responses of the system with and without wind speed sensor. The simulation case is similar for both conditions. In first place, the wind speed is simulated with the initial value of $5.3m/s$. After 60 seconds, a square wave wind speed variations of amplitude $1.5m/s$, 100 seconds period and a noise component of variance 0.025 and sampling time of $0.1s$ was selected as wind speed profile. From our hypothesis, the wind speed variation will be slow compared with the generator speed variations and all obtained equations will operate propertly.
During the simulations, there are particularly two important phases. The first phase (between 0 and 10s) is concerned with the initialization of the z estimator. After this, the RLSA starts its execution. The second phase starts at t=25 s. In this period, the control strategy is activated and the transient response that is evidenced for this instant is originated by the integrator resetting for the linear speed controller. Once it happens, the system has all the control strategies under excecution, including the optimal reference generation by solving (17).
In Figure 4, it can be seen the wind speed and its "filtered" version or, specifically, the effective wind speed that will interact with the turbine. At the same time, the values of $\hat{z}$ and the theoretical values of C_p and λ are shown on the basis of the wind turbine model parameters.
From the obtained results, it can be seen that the transient response of the generator speed presents slightly better performance (in terms of overshoot and setting time) when the wind speed is measured than in the wind sensorless case, as well as a better tracking over the optimal C_p and λ values, but the sensorless solution still offers stability and good performance in terms of power extracted to the turbine, and only deteriorated tracking of the optimal C_p under high wind speed variations.
One fact that is noticed is that both techniques assert to track the optimal C_p, demonstrating the good behavior of the internal control strategies, as well as the efficiency of the online estimation algorithms and the optimal reference generation.
As a conclusion, knowing the wind speed obviously yields better dynamical performances, but the proposed approach is good enough to being considered in case of a damaged sensor or imprecise wind speed measurement.

V. Conclusion

In this paper was proposed an optimal control strategy for wind power generation systems without wind speed measurement and having uncertain information of the power characteristic polynomial. The obtained results, based in the estimation of the power characteristic with a Kalman-like estimator and the adjustment of the power curve polynomial with a Recursive Least-Square Algorithm, allow to find an optimal electrical generator speed reference that takes the system to operate close to the optimal power generation point. The algorithm was tested for turbulent and variant

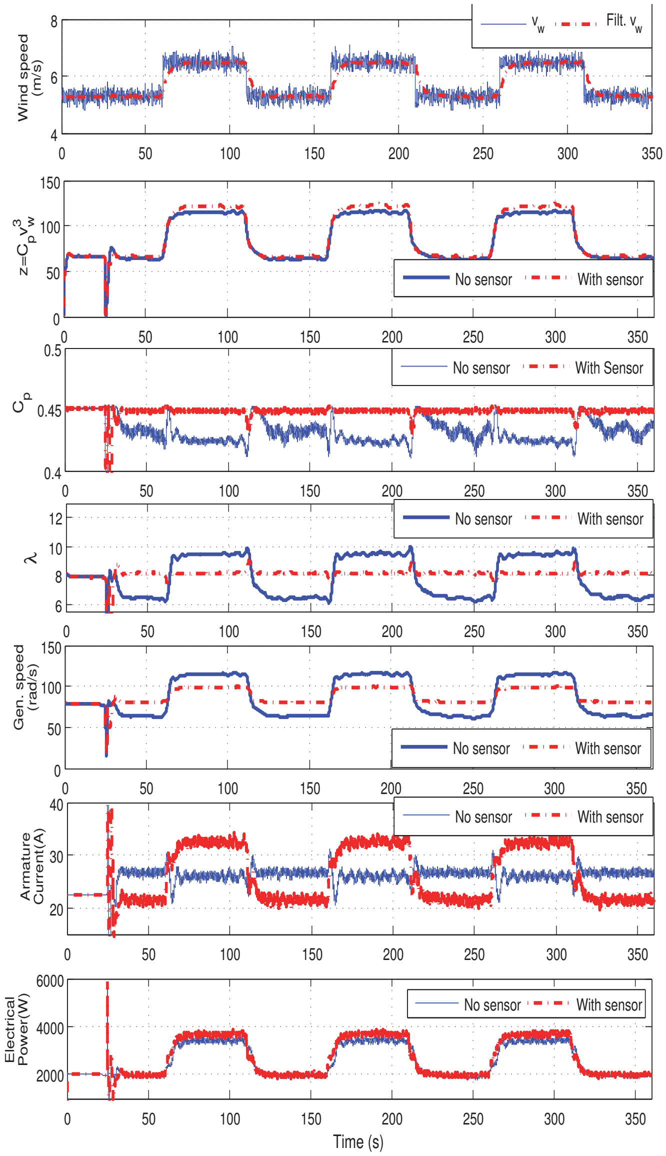

Fig. 4. Performance of the power system with and without wind speed measurement

wind speed, and the results were compared with the same system but operating with wind speed measurement and power coefficient(C_p)value estimation in real time. It has been seen that the proposed technique can give reliable and comparable results, and consequently, that if can for instance be used in situations in which the wind speed sensor is damaged or there are uncertainties over its measure. In future works, the integration of higher power wind turbines to the grid and with other classes of alternative power sources, as well as some mechanisms for improving the optimal C_p tracking (initial values or better adaptibility of polynomial for the RLSA algorithm) will be analyzed.

REFERENCES

[1] L. Chen, F. Ponta, and L. Lago, "Perspectives on innovative concepts in wind-power generation," *Energy for Sustainable Development*, vol. 15, no. 4, pp. 398 – 410, 2011.

[2] E. Hau, *Wind Turbines: Fundamentals, Technologies, Applications, Economics*. Springer, 2006.

[3] S. Heier, *Grid Integration Of Wind Energy Conversion Systems*. Wiley, 2006.

[4] I. Munteanu, A. Bratcu, N. Cutululis, and E. Ceanga, *Optimal Control Of Wind Energy Systems: Towards a Global Approach*. Springer, 2008.

[5] G. Spagnuolo, G. Petrone, M. Vitelli, J. Calvente, C. Ramos-Paja, R. Giral, E. Mamarelis, and E. Bianconi, "A fast current-based mppt technique employing sliding mode control," *Industrial Electronics, IEEE Transactions on*, vol. PP, no. 99, p. 1, 2012.

[6] A. E. Magri, F. Giri, A. Elfadili, and L. Dugard, "Wind sensorless control of wind energy conversion system with pms generator," in *Proc American Control Conf, Montreal Canada*, 2012.

[7] K. Busawon, L. Dodson, and M. Jovanovic, "Estimation of the power coefficient in a wind conversion system," in *Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC '05. 44th IEEE Conference on*, pp. 3450 – 3455, dec. 2005.

[8] G. Son, H.-J. L. Lee, and J.-W. Park, "Estimation of wind turbine rotor power coefficient using rmp model," in *Industry Applications Society Annual Meeting, 2009. IAS 2009. IEEE*, pp. 1 –8, oct. 2009.

[9] P. Mateljak, V. Petrovic, and M. Baotic, "Dual kalman estimation of wind turbine states and parameters," in *18th Conference of Process Control, 2011.*, pp. 85–91, 2011.

[10] K. Z. Ostergaard, P. Brath, and J. Stoustrup, "Estimation of effective wind speed," *Journal of Physics: Conference Series*, vol. 75, no. 1, p. 012082, 2007.

[11] K. Johnson, L. Pao, M. Balas, and L. Fingersh, "Control of variable-speed wind turbines," *Control Systems Magazine, IEEE*, vol. 26, no. 3, pp. 70–81, 2006.

[12] J. Laks, L. Pao, and A. Wright, "Control of wind turbines: Past, present, and future," in *American Control Conference, 2009. ACC '09.*, pp. 2096–2103, 2009.

[13] M. Chinchilla, S. Arnaltes, and J. Burgos, "Control of permanent-magnet generators applied to variable-speed wind-energy systems connected to the grid," *Energy Conversion, IEEE Transactions on*, vol. 21, pp. 130 – 135, march 2006.

[14] F. Blaabjerg, Z. Chen, R. teodorescu, and F. Iov, "Power electronics in wind turbine systems," in *Power Electronics and Motion Control Conference, 2006. IPEMC 2006. CES/IEEE 5th International*, pp. 1–11, 2006.

[15] L. Barote and C. Marinescu, "Modeling and operational testing of an isolated variable speed pmsg wind turbine with battery energy storage," *Advances in Electrical and Computer Engineering*, vol. 12, no. 2, pp. 81 – 88, 2012.

[16] J. Sandoval-Moreno and E. Franco-Mejia, "Performance comparison between hinf and pid control strategies applied to boost power converters," in *IEEE ANDESCON,2010*, Jul. 2010.

[17] W. Leonhard, *Control of Electrical Drives*. Springer, 2001.

[18] A. Isidori, *Nonlinear control systems*. Springer, 1995.

[19] A. Ticlea and G. Besancon, "Observer scheme for state and parameter estimation in asynchronous motors with application to speed control," *European Journal of Control*, vol. 12, pp. 1–13, 2006.

[20] G. Besancon and A. Ticlea, "An immersion-based observer design for rank-observable nonlinear systems," *IEEE Transactions on Automatic Control*, vol. 52, pp. 83–88, 2007.

[21] G. Besancon, *Nonlinear observers and applications*. Springer, 2007.

[22] R. Stengel, *Optimal Control and Estimation*. Dover, 1994.

[23] S. Skogestad and I. Postlethwaite, *Multivariable Feedback Control*. Wiley, 2006.