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Title Grey Predictor Reference Model For Assisting Particle Swarm Optimization

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Abstract

This paper proposes an approach of forming the average performance by Grey Modeling, GM, and use an average performance as reference model for doing evolutionary computation with error type performance index. The idea of the approach is to construct the reference model based on the performance of unknown systems when users apply evolutionary computation to fine-tuning the control systems with error type performance index. We apply this approach to particle swarm optimization for searching the optimal gains of baseline PI controller of wind turbines operating at the certain set point in Region 3. In the numerical simulation part, the corresponding results demonstrate the effectiveness of Grey Modeling.

1. INTRODUCTION

The applications of intelligent optimization have been proposed and shown the strengths in literature [1]-[3]. Unlike the gradient-based optimization methods, these random optimization methods less likely get trapped at the local optimum. Compared with other optimization algorithms, particle swarm optimization (PSO) is better suited for some applications. First, PSO consists of a simpler concept and elegant paradigm, which means PSO is more computationally efficient. Moreover, PSO has memory and knowledge of optimum which is kept by all particles. Thanks to the advantages of PSO, we choose PSO assisted by Grey Predictor to solve the optimization problems of control systems design. The applications of the combination of PSO and Grey predictor can also be seen [9]-[10].

In general, integral of square error (ISE), integral of absolute error (IAE), integral of time weighted absolute error (ITAE) and integral of time weighted square error (ITSE) are commonly used performance indexes to evaluate the performance of control systems [11]-[13]. However, following these error-integral type performance indexes, the performance of control systems are with long sustained oscillation. To overcome these drawbacks, different performance indexes are proposed.

In 1958 M. A. Aizerman introduced a type of performance index, the general performance index [18], with differential equations to define the desired system models:

$$I = \int_0^\infty \left[e(t)^2 + \tau_1^2 \dot{e}(t)^2 + \tau_2^4 \ddot{e}(t)^2 + \cdots + \tau_n^{2n} \left(\frac{d^n e(t)}{dt^n} \right)^2 \right] dt$$

Z. V. Rekasius utilized the general performance index for analytical design of control systems in 1961 [18]. Nevertheless, it is a tough task to derive the ideal model of the performance index of the type of (1) for higher-order models, complex systems and even uncertain systems. There are also limitations imposed on the ideal model and the performance index also burdens some restrictions on deriving ideal model.

Due to the disadvantages of the general performance index, Z. V. Rekasius presented another way to form the performance index as [18]:

$$I = \int_0^{\infty} \left[x(t) + \sum_{i=1}^{k} \tau_i \frac{d^i x(t)}{dt^i} \right]^2 dt, \qquad k < n$$

In order to minimize the performance index above, the optimum system would be consequently derived as:

$$x(t) + \sum_{i=1}^{k} \tau_i \frac{d^i x(t)}{dt^i} = 0, \qquad k < n$$

As a result, the transfer function of the closed-loop system (Fig. 1) can stand for the ideal model as:

$$\frac{C(s)}{R(s)} = \frac{1}{1 + \sum_{i=1}^{k} \tau_i s^i}$$

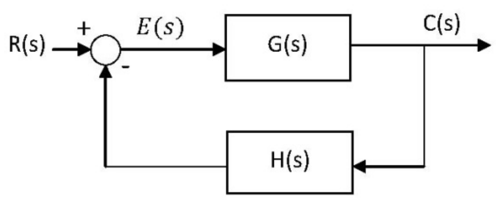

Figure 1 Block diagram of feedback system

Even though this type of performance index is a possibility of obtaining ideal model, there is no rule for determining how many terms should be used and what values the variable, τi, is.

Another type of performance index which shares the same concept with linear quadratic regulator (LQR) is described as [14]:

$$I = \int_0^{\infty} \left\{ \left(y(t) - z(t) \right)^2 + \alpha u(t)^2 \right\} dt$$

where y(t) is , z(t) is and u(t) is

Since this type of performance index comprises a desired function z and undetermined variable α, control engineers need to construct the desired function and determine the optimal α before going through the optimization process. See for instance Refs. [13]-[17].

Some researchers presented another approach [19] in order to take into account the overshoot, settling time and robustness simultaneously.

In this paper, a Grey-modeling approach is presented for predicting the performance based on the behavior of the optimized system by PSO with error-integral type performance indexes. Following the predicted performance, the control system is then optimized by PSO again. We take our recent research, control design of wind turbine, as an instance. The paper is organized in such a way that PSO, Grey Predictor, simulation environment and control structure are briefly reviewed, and finally the results of numerical simulation are compared to show the improvement.

2. MODEL DESCRIPTION

In this section, we first review particle swarm optimization, grey theory and the control structure. Then we explain how to implement the whole design process in the simulation environment.

Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a stochastic optimization originated from social behaviors of bird flocking or fish schooling and was first proposed by Kennedy, Eberhart and Shi in 1995[7]-[8]. Unlike conventional optimization approaches, PSO depends on the trajectories of a group of potential solutions as known as “particles” to search the optimum.

Particle Swarm Optimization uses velocity vector of each particle to update the position of each particle in the swarm [4]. The PSO algorithm is described as the following steps:

1. Start with an initial set of particles, usually randomly distributed throughout the design space.
2. Determine the velocity of each particle based on the following equation:

$$v^i_{k+1} = K[w v^i_k + c_1 r_1 (p^i - x^i_k) + c_2 r_2 (p^g_k - x^i_k)]$$

where w is called inertial weight, $\mathbf{p}^i$ is currently local optimum of particle i and $\mathbf{p}^g{}_k$ is currently global optimum in the swarm at iteration k. The coefficients c_1 and c_2 are respectively called cognitive and social parameters and r_1 and r_2 are random numbers between 0 and 1.

3. Update the position of particle i by the following equation:

$$x^i_{k+1} = x^i_k + v^i_{k+1}$$

4. Back to step 2 and repeat until the convergence criteria is met or total iterations are done.

To improve the performance of PSO, Eberhart and Shi suggested the inertia weight which linearly changes from 0.9 to 0.4 [5]-[6]. The inertia weight can be represented as:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter$$

where w_{max} and w_{min} denote the maximum and minimum of w, respectively and $iter_{max}$ is the maximum number of iterations and iter is the current iteration. The constriction factor can be represented as:

$$K = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|} \quad \varphi = c1 + c2, \quad \varphi > 4$$

K is generally considered to be 0.729 with c1=c2=2.05.

Grey Predictor

The first research entitled "The Control Problem of Grey Systems" in the journal, Systems and Control Letters, was initiated by Ju-Long Deng in 1982. For simplicity, the "black" is usually represented as lack of information and the "white" represented as known information. Hence, the information that is either incomplete or partly known is called "Grey". We can roughly conclude the incomplete information as four possible categories [20]:

1. The information of elements (or parameters) is incomplete
2. The information on structure is incomplete
3. The information on boundary is incomplete
4. The behavior information of movement is incomplete

In general, the grey modeling is through building GM(β,γ) model as known as Grey Model, where β is the order of the differential equation and γ is the number of variables. Grey theory has been successfully applied for solving control problems [21]-[22] and in wind energy industry [23]-[26].

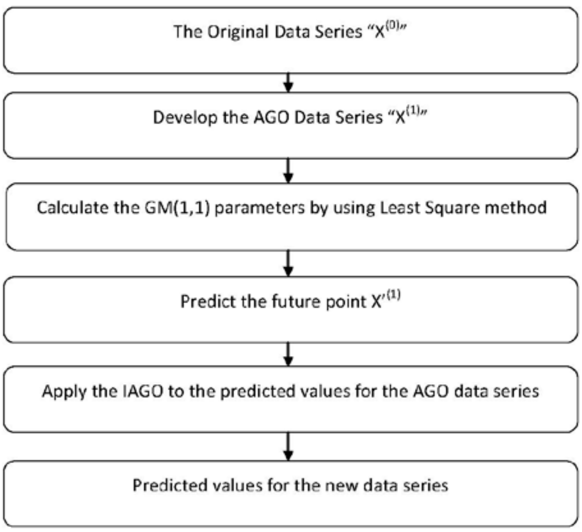

Figure 2: Flowchart of Grey Modeling

Grey prediction process is as following and in Fig. 2:

1. Accumulated Generation Operation (AGO):

This step is to map the original set of data $X^{(0)}$ into a new set $X^{(1)}$ with less noise and randomness than original data set; therefore, the new data set characterizes a smoother pattern than original pattern. The equation for generating the AGO series is as follows:

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), \quad \forall k = 1,2,...n$$

2. Grey Differential Equation:

By deriving the differential equation, this step is to build the relation between the dependent variables and independent ones. This differential equation, called GM(1,1), with one independent variables and no dependent variable generally is expressed as:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b$$

where X represents the independent variable. The coefficients "a" and "b" are determined by using least square method in the next step.

3. Equation Parameters Calculations:

This step is to calculate the parameters "a" and "b" of GM(1,1)

4. Prediction Equation for the GM(1,1):

This step is to build the predicted AGO series which can be described as:

$$\hat{X}^{(1)}(i+1) = (X^{(0)}(1) - \frac{b}{a})e^{-ai} + \frac{b}{a}$$

5. Inverse Accumulated Generating Operation (IAGO):

This final step is to map the predicted AGO set to original series. The process is as following:

$$\hat{X}^{(0)}(0) = \hat{X}^{(1)}(1)$$

$$\hat{X}^{(0)}(i+1) = \hat{X}^{(1)}(i+1) - \hat{X}^{(1)}(i) \quad \forall i = 1,2,3...$$

Dynamics Systems, Control Design, Optimization and Simulation Environment

We investigate the impact of grey modeling on PSO in the control design of wind turbine operating in region 3. The turbine model which is a horizontal-axis Control Advanced Research Turbine (CART3), 3-blade, upwind, variable-speed and 600 KW is located at National Renewable Energy Laboratory (NREL) [27]. To be consistent with the control system in the report from NREL, the PI rotor collective pitch controller is considered [29]. The history of utilizing PID controller for wind turbine can be seen in Refs. [30]-[31]. In region 3, the control objective is to regulate the power at a constant level by adjusting the blade pitch [29] (i.e., the rotor speed should be regulated to a set point). Fig. 3 shows the wind turbine model with PI controller, PSO and Grey Predictor.

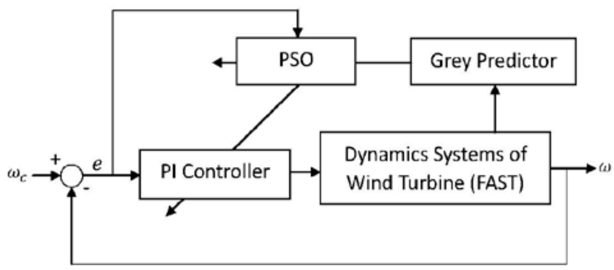

Figure 3: Block diagram of control systems optimized by PSO with Grey predictor for wind turbine rotor speed regulation; where e=ω_c - ω, ω is the rotor speed

(rpm), and ω_c is the commanded or rated rotor speed (rpm).

The parameters of PSO are in Table 1.

Parameters of PSO	
Iteration	25
Popular Size	10
Range of k_P	[0, 1.5708]
Range of k_I	[0, 1.5708]

The error-integral type performance indexes are:

$$ISE=\int_0^{t_f} e(t)^2 dt$$

$$ITSE=\int_0^{t_f} t * e(t)^2 dt$$

$$IAE=\int_0^{t_f} |e(t)| dt$$

$$ITAE=\int_0^{t_f} t * |e(t)| dt$$

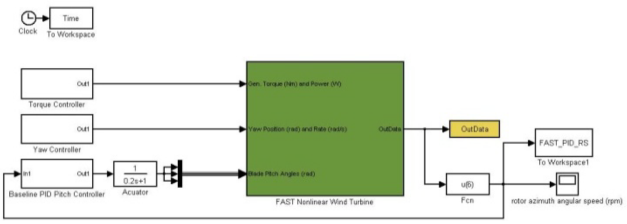

Figure 4: Simulink model of FAST with PI controller and actuator in loop

The block diagram of PI controller with the actuator for the wind turbine is shown in Fig. 5. The simulation environment is the open-source code FAST (Fatigue, Aerodynamics, Structures, and Turbulence) which was developed at Oregon State University and investigated and modified by National Renewable Energy Laboratory (NREL) [27].

3. NUMERICAL SIMULATION

Figuer shows the step-wind profile which is used in this study for searching the optimal gains of PI controller; the step-wind profile is similar to that in the paper [28]. For improving Grey predictor, we increase the time span of step-wind profile. We choose error-integral type performance index, ISE, ITSE, IAE and ITAE.

Numerical simulations are carried out with MATLAB and FAST code to show and we compare the performances of the error-integral type performance indexes without and with assistance of Grey predictor.

We use the proportional gain, kP=0.380 and integral gain, kI=0.136 for baseline-PI controller [29]. The nominal rotor angular speed is □c=41.7 (rpm) and initial pitch angle is θ0 = 110.

The Fig. and Fig. show the comparison of performance of the control system optimized without and with grey predictor.

Table2. Comparison of gains of PI rotor collective pitch controller

Ref. [29]	KP=0.380 KI=0.136
ISE	KP=1.4900 KI=1.5708
ISE + Grey Predictor	KP=0.6615 KI=0.2078
ITSE	KP=1.4393 KI=1.5708
ITSE + Grey Predictor	KP=0.7767 KI=0.1299
IAE	KP=0.9733 KI=1.2192
IAE + Grey Predictor	KP=0.6605 KI=0.2095
ITAE	KP=0.9078 KI=1.1597
ITAE + Grey Predictor	KP=0.6087 KI=0.2196

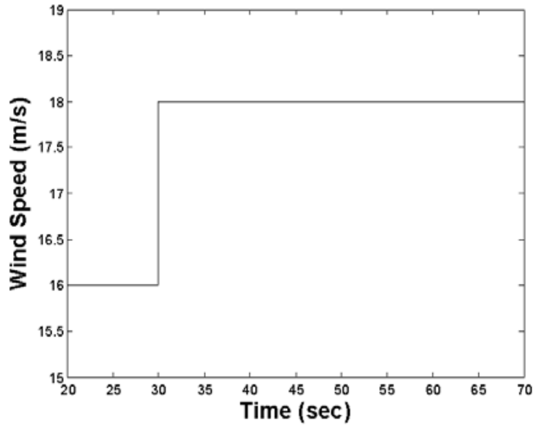

Figure 5: Step wind profile

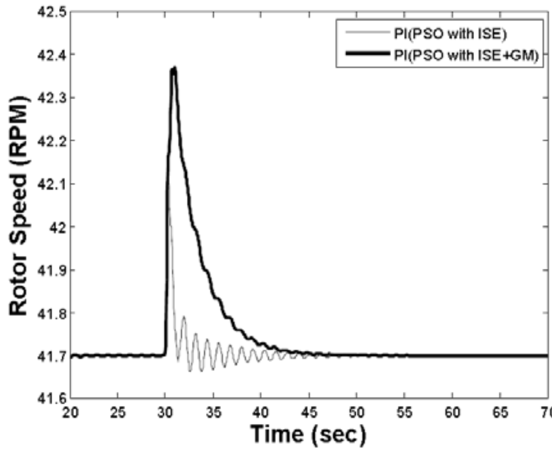

Figure 6: Performance of CART3 with PI(PSO with ISE) and PI(PSO with ISE+GM)

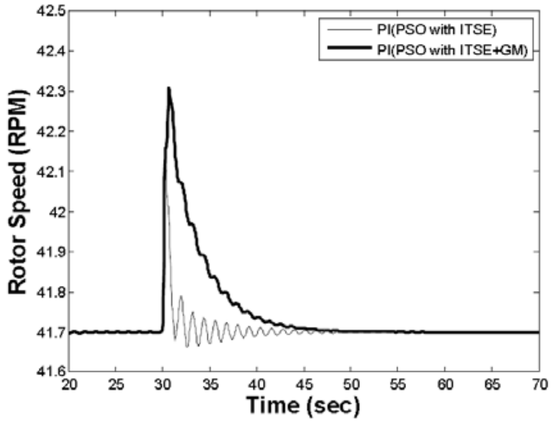

Figure 7: Performance of CART3 with PI(PSO with ITSE) and PI(PSO with ITSE+GM)

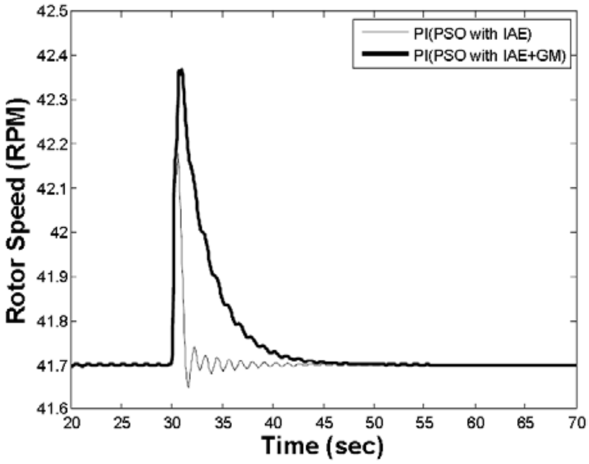

Figure 8: Performance of CART3 with PI(PSO with IAE) and PI(PSO with IAE+GM)

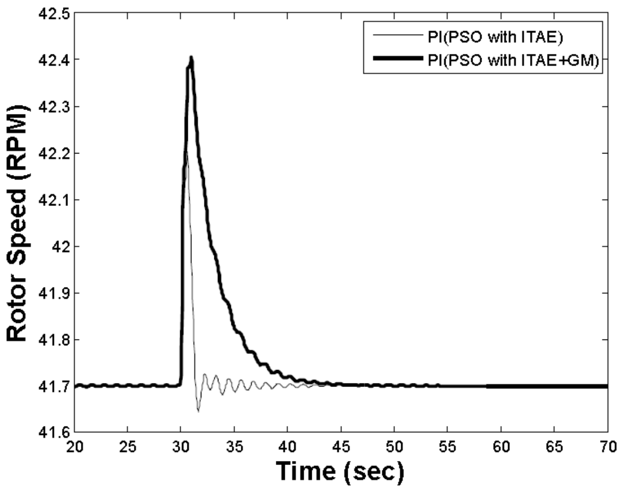

Figure 9: Performance of CART3 with PI(PSO with ITAE) and PI(PSO with ITAE+GM)

4. CONCLUSION

A Grey predictor for assisting intelligent optimization is introduced. The control system is optimized by PSO with Grey predictor. Based on the simulation results, the performance of the PI controller with Grey predictor is obviously with less oscillation, especially when wind speed is higher. However the overshoot of control system with Grey predictor is bigger and settling time of control system with Grey predictor is longer as well. For different control sakes, control engineers probably face the tradeoff and have to make a decision. This paper provides a direction of predicting performance of control systems and of designing control systems with less oscillation, hence less stress on a physical system under consideration.

REFERENCES

[1] Zongzhao Zhou, Yew Soon Ong, Prasanth B. Nair, Andy J. Keane and Kai Yew Lum, "Combining Global and Local Surrogate Models to Accelerate Evolutionary Optimization," IEEE Transactions on Systems, Man, and Cybernetics- Part C: Application and Review, Vol. 37, No. 1, January 2007

[2] Zwe-Lee Gaing, "A Particle Swarm Optimization Approach for Optimum Design of PID Controller in AVR System," IEEE Transactions on Energy Conversion, Vol. 19, No. 2, June 2004

[3] David B. Fogel, "An Introduction to Simulated Evolutionary Optimization," IEEE Transaction on Neural Networks, Vol. 5, No. 1, January 1994

[4] J. Kennedy and R. C. Eberhart with Y. Shi, "Swarm Intelligence," Part 2- Chap. 7, pp. 287-324, Morgan Kaufmann Publishers, 2001

[5] R.C. Eberhart and Y. Shi, "Comparing Inertia Weights and Constriction Factors in Particle Swarm Optimization," Proceedings of the ICEC, 2000

[6] Maurice Clerc, "The Swarm and the Queen: Towards a Deterministic and Adaptive Particle Swarm Optimization," Proceedings of the 1999 ICEC, Washington, DC, pp 1951-1957

[7] R. C. Eberhart and J. Kennedy, "A New Optimizer Using Particle Swarm Theory," Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, pp. 39-43, 1995.

[8] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization," Proceedings of the 1995 IEEE ICEC , Perth, Australia, pp. 1942-1948

[9] Guo-Dong Li, Shiro Masuda, Daisuke Yamaguchi and Masatake Nagai "A New Reliability Prediction Model in Manufacturing systems" IEEE Transactions On Reliability,Vol.59,No.1, MARCH 2010

[10] Wei Sun and Yujing Yan, "The Model Based on Grey Theory and PSO for Electricity Consumption Forecasting" International Conference on Intelligent Computation Technology and Automation, 2008

[11] D. Maiti, A. Acharya, M. Chakraborty, A. Konar and R. Janarthanan, " Tuning PID and $PI^{\lambda}D^{\delta}$ Controllers using the Integral Time Absolute Error Criterion," Information and Automation for Sustainability, 2008

[12] Matthew J. Wade and Michael A. Johnson, "Towards Automatic Real-Time Controller Tuning and Robustness," Industry Application Conference, 2003. 38th IAS Annual Meeting, December 2003

[13] H. H. Rosenbrock, "The Integral-of-error-squared Criterion for Servo Mechanisms," Proceedings of the IEE-Part B: Radio and Electronic Engineering, Vol. 102, pp. 602- 607, 1955

[14] B. Ramaswami and K. Ramar, "Optimal Servo Problems With Polynomial Desired Outputs And A Modified Performance Index" IEE-IERE Proceedings - ,Vol.10,No.3, P.79-82,May-June 1972

[15] B. Ramaswami and K. Ramar, "A New Method of Solving Optimal Servo Problems" IEEE Transactions on Automatic Control,Vol.17, No.1, P.131-135, Feb 1972

[16] B. Ramaswami and K. Ramar, "New Method of Solving Optimal Servo Problems reducible to regulator problems" IEEE Transactions on Automatic Control,Vol.15, No.4, P.500-501, Aug 1970

[17] E. Kreindler, "On Servo Problems Reducible to Regulator Problem" IEEE Transactions on Automatic Control,Vol.14,No.4, P.413-415 ,Aug. 1969

[18] Z.V. Rekasius, "A General Performance Index For Analytical Design of Control Systems" Automatic Control, IRE Transactions,Vol.6,No.2, P.217-222, 1961

[19] Pen Chen Chou and Son Chin Hsieh, "Neural Assisted PI/PID Controller Design for a Motor Control System," IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, 2005.

[20] Sifeng Liu and Yi Lin, *Grey Information*, Springer, 2005

[21] Shiuh-Jer Huang and Chien-Lo Huang, "Control of an Inverted Pendulum Using Grey Prediction Model" IEEE Transactions on Industry Application,Vol.36, No.2, March/April 2000

[22] Ching-Chang Wong and Chia-Chong Chen, "A Simulated Annealing Approach to Switch Grey Prediction Fuzzy Control System Design" International Journal of Systems Science, Vol. 29, No. 6, pp. 637-642, 1998

[23] Y. M. Atwa and E. F. El-Saadany, "Annual Wind Speed Estimation utilizing Constrained Grey Predictor" IEEE Transaction on Energy Conversion, Vol. 24, No. 2, June 2009

[24] Peng Kuo, "Research of a New MPPT Strategy Based on Gray Wind Speed Prediction" Second International Symposium on Knowledge Acquisition and Modeling, 2009

[25] T. H. M. El-Fouly, E. F. El-Saadany and M. M. Salama, "Improved Grey Predictor Rolling Models for Wind Power Prediction" IET Gener. Transm. Distrib., 1, (6), pp. 928-937, 2007

[26] T. H. M. El-Fouly, E. F. El-Saadany and M. M. A. Salama "Grey Predictor for Wind Energy Conversion Systems Output Power Prediction" IEEE Transactions On Power Systems,Vol.21,No3,August 2006

[27] National Renewable Energy Laboratory, http://wind.nrel.gov/public/Awright/CART%20FAST%20models/CART3/

[28] S. A. Frost, M. J. Balas, and A. D. Wright, "Direct Adaptive Control of a Utility-Scale Wind Turbine for Speed Regulation," International Journal of Robust and Nonlinear Control, 19(1): 59-71, Jan. 2009

[29] A. D. Wright and L. J. Fingersh, "Control Design, Implementation, and Initial Tests," NREL Report No. TP-500- 42437, National Renewable Energy Laboratory, 2008

[30] O. Wasynczuk, D.T. Man, and J. P. Sullivan, "Dynamic Behavior of a Class of Wind Turbine Generators during Random Wind Fluctuations," IEEE Transactions on Power Apparatus and Systems, 100, pp. 2837-2845, 1981.

[31] J. M. Kos, "On Line Control of a Large Horizontal Axis Energy Conversion System and its Performance in a Turbulent Wind Environment," Proceedings of the 13th Intersociety Energy Conversion Engineering Conference, pp. 2064-2073, 1978.