Adaptive PID Control of Wind Energy Conversion Systems Using RASP1 Mother Wavelet Basis Function Networks

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Abstract—In this paper a PID control strategy using neural network adaptive RASP1 wavelet for WECS's control is proposed. It is based on single layer feedforward neural networks with hidden nodes of adaptive RASP1 wavelet functions controller and an infinite impulse response (IIR) recurrent structure. The IIR is combined by cascading to the network to provide double local structure resulting in improving speed of learning. This particular neuro PID controller assumes a certain model structure to approximately identify the system dynamics of the unknown plant (WECS's) and generate the control signal. The results are applied to a typical turbine/generator pair, showing the feasibility of the proposed solution.

Keywords—Adaptive PID Control, RASP1 Wavelets, Wind Energy Conversion Systems.

I. INTRODUCTION

WIND energy conversion systems (WECS's) have in the past two decades been the object of strong interest as a viable source of electrical energy. Various electromechanical schemes for generating electricity from the wind have been suggested, but the main drawback is that the resulting system is highly nonlinear, and thus a nonlinear control strategy is required to place the system in its optimal generation point. Among others, sliding mode control [1] and fuzzy systems [2] have been proposed as feasible control alternatives.

Many authors [3] and [4] have suggested neural networks as power full building blocks for nonlinear control strategies due to their ability to uniformly approximate arbitrary input-output mappings on closed bounded subsets. The idea of neuro control is to first process an identification model that approximates the unknown dynamics of the plant in which the parameters of the neural network are adjusted off-line. The Parameters of the proposed predictive controls are then adjusted on-line within a feedback loop based on algebraic computations following the sampled information. The most famous topologies for this purpose are multilayer perceptron (MLP) and radial basis function (RBF) networks [5]. A neural-network-based structure for WECS's control, that It consists of two combined control actions: a supervisory control and an RBF network-based adaptive controller has proposed in [6].

This paper proposes a adaptive PID controller using neural network frame RASP1 wavelets for WECS's control. It consists of a single layer feedforward neural network with hidden nodes of adaptive wavelet functions controller and an infinite impulse response (IIR) recurrent structure. The IIR is combined by cascading to the network to provide double local structure resulting in improving speed of learning.

II. WIND ENERGY CONVERSION SYSTEMS

In this paper the most common type of wind turbine, that is, the horizontal-axis type, is considered.

The output mechanical power available from a wind turbine is [1].

$$P = 0.5\rho C_p (V_\omega)^3 A \tag{1}$$

Where ρ is the air density $[kg/m^3]$, A is the area swept by the blades $[m^2]$, and V_ω is the wind speed $[m/s]$, C_p is called the "power coefficient," and is given as a nonlinear function of the parameter $\lambda = \omega R/V_w$, where R is the radius of the turbine $[m]$ and ω is the rotational speed $[rad/\sec]$. Usually C_P is approximated as $C_P = \alpha\lambda + \beta\lambda^2 + \gamma\lambda^3$, where α, β and γ are constructive parameters for a given turbine.

It can be pointed that $C_{P\max}$, the maximum value for C_P , is a constant for a given turbine [6]. That value, when replaced in (1), gives the maximum output power for a given wind speed. This corresponds to an optimal relationship λ_{opt} between ω and V_ω . The torque developed by the wind turbine is:

$$T_l = 0.5\rho \left(\frac{C_p}{\lambda} \right)(V_\omega)^2 \pi R^2 \tag{2}$$

Fig. 1 shows the torque/speed curves of a typical wind turbine, with V_ω as a parameter. Note that maximum generated power ($C_{P\max}$) points do not coincide with maximum developed torque points.

Optimal performance is achieved when the turbine operates at the $C_{P\max}$ condition. This will be control objective in this paper.

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International Journal of Electrical and Computer Engineering
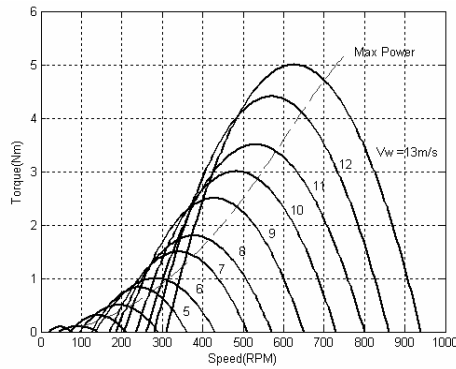Vol:2, No:1, 2008

Fig. 1 Torque/speed curves (solid) of a typical wind turbine. The curve of $C_{P\,max}$ is also plotted (dotted)

Here the double output induction generator (DOIG) is considered. In this generator, slip power is injected to the AC line using a combination of rectifier and inverter known as a static Kramer drive. Changes on the firing angle (α) of the inverter can control the operation point of the generator, in order to develop a resistant torque that places the turbine in its optimum (maximum generation) point. The torque developed by the generator/Kramer drive combination is [6]:

$$T_g = f(\omega, \cos(\alpha)) \qquad (3)$$

The dominant dynamics of the whole system (turbine plus generator) are those related to the total moment of inertia. Thus ignoring torsion in the shaft, generator's electric dynamics, and other higher order effects, the approximate system's dynamic model is:

$$\omega^\bullet = 1/J[T_l(\omega, V_\omega) - T_g(\omega, \alpha)] \qquad (4)$$

where J is the total moment of inertia. Regarding (2) and (3), this is highly nonlinear model. Moreover, it is well known that certain generator parameters are strongly dependent on factors such as temperature and aging. Thus a nonlinear adaptive control strategy seems very attractive. Its objective is to place the turbine in its maximum generation point ($Cp\,max$), i.e. ω_{opt}, T_{lopt}, in despite of wind gusts and generator's parameter changes.

The general form of (4) is $\omega^\bullet = h(\omega, \alpha)$, where h a nonlinear function is accounting for the turbine and generator characteristics. The system is usually designed so that the maximum turbine torque corresponds to 0.5 to 0.7 of the peak generator torque. In that region a simple linearization of the generator expression can be made. The resulting expression after linearization of the generator characteristics for the whole system is then $\omega^\bullet = f(\omega) + bu$. Here, f is a nonlinear function, b is a constant and $u = \cos(\alpha)$.

III. PROPOSED CONTROL STRATEGY

A. Structure and Algorithms

Before beginning tracking operation using a neuro network based PID controller, the unknown nonlinear WECS must be identified according to a certain model. In this particular identification process, the model consists of a neural network topology with the wavelet transform embedded in the hidden units. In cascades with the network is a local infinite impulse response (IIR) block structure as shown in Fig. 2. The algorithm of neural network adaptive wavelets is similar to those in [8] where any desired signal $y(t)$ can be modeled by generalizing a linear combination of a set of RASP1 daughter wavelets $h_{a,b}(t)$, where $h_{a,b}(t)$ are generated by dilation, a, and translation, b, from a mother wavelet :

$$h_{a,b}(t) = h(\frac{t-b}{a}) = \frac{\tau}{(\tau^2 + 1)^2} \qquad (5)$$

with the dilation factor $a > 0$.

That $\dfrac{\partial h_{a,b}(t)}{\partial b} = \dfrac{1}{a}[\dfrac{3\tau^2 - 1}{(\tau^2 + 1)^3}]$ and $\tau = \dfrac{t-b}{a}$

Assume that the network output function satisfies the admissibility condition and that the network sufficiently distributes K sets of the mother wavelet basis functions, evenly portioning the interest region. The approximated signal of the network $\hat{y}(t)$ can be modeled by [9]:

$$\hat{y}(t) = \sum_{i=0}^{M} c_i z(t-i)u(t) + \sum_{j=1}^{N} d_j \hat{y}(t-j)v(t) \qquad (6)$$

where

$$z(t) = \sum_{k=1}^{K} w_k h_{a_k,b_k}(t) \qquad (7)$$

K is the number of wavelets, w_k is the kth weight coefficient. M and c_j are the number of feed forward delays and coefficient of the IIR filter, respectively , N and d_j are the number of feed back and recursive filter coefficients , respectively. The signals $u(t)$ and $v(t)$ are the input and co-input to the system at time t, respectively. Input $v(t)$ is usually kept small for feedback stability purposes.

The neural network parameters a_k, b_k, c_i, w_k and d_j can be optimized in the LMS sense by minimizing a cost function or the energy function, E, over all time t.

Thus,

$$e(t) = y(t) - \hat{y}(t) \qquad (8)$$

is a time varying error function at time t, where $y(t)$ is the desired (target) response. The energy function is defined by

$$E = \frac{1}{2} \sum_{t=1}^{T} e^2(t) \qquad (9)$$

World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:2, No:1, 2008

To minimize E we may use the method of steepest descent and each coefficient vector $\underline{a}, \underline{w}, \underline{b}, \underline{c}$ and $\underline{d}$ of the network is updated in accordance with the rule

$$\underline{f}(n+1) = \underline{f}(n) + \mu_f \Delta \underline{f} \qquad (10)$$

Where the subscripted μ_f values are fixed learning rate parameter and $\Delta \underline{f} = -\partial E / \partial f$.

B. System Model and PID Controller Design

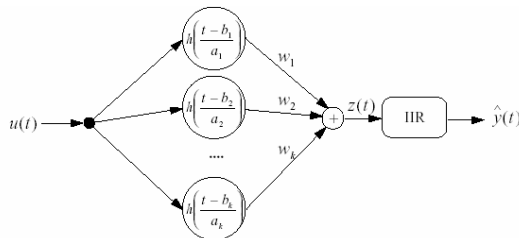Consider a general SISO dynamical system similar to (4) is represented by the state equations

$$x^\bullet = f(x(t), u(t), t) \qquad (11)$$
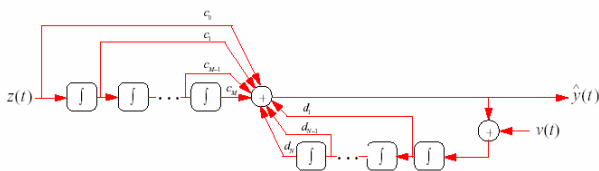
$$y(t) = g(x(t), t) \qquad (12)$$

That in discrete domain rewritten following as:

$$x(k+1) = f(x(k), u(k), k) \qquad (13)$$

$$y(k) = g(x(k), k)$$

(a)

(b)

Fig. 2 IIR Adaptive wavelet network structure: (a) neural network architecture (b) IIR model

where $x(k) \in R^n$ and $u(k), y(k) \in R$. Further, let the unknown functions $f, g \in C^1$. The only accessible data are the input u and output y. It has been [9] that if the linear system around the equilibrium state is observable, an input-output representation exists which has the form

$$\begin{aligned} y(k+1) = \varphi(y(k), y(k-1), ..., y(k-n+1), \\ u(k), u(k-1), ..., u(k-n+1)) \end{aligned} \qquad (14)$$

i.e. a function $\varphi(.)$ exists that maps $y(k)$ and $u(k)$, and their $n-1$ past values, into $y(k+1)$. In view of this, a neural network model $\hat{\varphi}$ can be trained to approximate φ over the domain interest. The considerations are based on the neural network controller design of the control system. The following alternative model of an unknown plant that can simplify the computation of the control input is described by the equation:

$$y(k+1) = \phi(y(k)) + \Gamma(y(k)).u(k) \qquad (15)$$

for a discrete-time process of one dimension where $y(k)$ and $u(k)$ denote the input and the output at the kth instant of time.

If the nonlinearity terms $\phi(.)$ and $\Gamma(.)$ are known exactly, the required control $u(k)$ for tracking a desired output $r(k+1)$ can be computed at every time instant using the formula

$$u(k) = \frac{r(k+1) - \phi(y(k))}{\Gamma(y(k))} \qquad (16)$$

However, if $\phi(.)$ and $\Gamma(.)$ are unknown, the idea is to use the neural network adaptive wavelets model to approximate the system dynamics i.e.,

$$\hat{y}(k+1) = \hat{\phi}(y(k), \Theta\phi) + \hat{\Gamma}(y(k), \Theta_\Gamma)u(k) \qquad (17)$$

Comparing the model of Eq. (17) with the one of Eq. (6) we can conclude that

$$\hat{\phi}(y(k), \Theta_\phi) = \sum_{j=1}^{N} d_j \hat{y}(k-j)v(k) \qquad (18)$$

$$\hat{\Gamma}(y(k), \Theta_\Gamma) = \sum_{i=0}^{M} c_i z(k-i) \qquad (19)$$

After the nonlinearities $\phi(.)$ and $\Gamma(.)$ are approximated by the two distinct neural network functions $\hat{\phi}(.)$ and $\hat{\Gamma}(.)$ with adjustable parameters, represented by Θ_ϕ and Θ_Γ respectively, the PID control $u(k)$ for tracking a desired output $r(k+1)$ can be obtained from:

$$u(k) = u(k-1) + P[\varepsilon(k) - \varepsilon(k-1)] + I\varepsilon(k) + D[\varepsilon(k) - 2\varepsilon(k-1) + \varepsilon(k-2)] \qquad (20)$$

where P, I, and D are proportional, integral, and differential gains, $u(k)$ is a plant input at kT, where T is a sampling interval, and

$$\varepsilon(k) = r(k) - y(k) \qquad (21)$$

P, I, D parameters are considered as part of the function of E and can be optimized and updated according to the cost function E of Eq. (9),

$$P(k) = P(k-1) + \mu_P e(k)\Gamma(k)(\varepsilon(k) - \varepsilon(k-1)) \qquad (22)$$

$$I(k) = I(k-1) + \mu_I e(k)\Gamma(k)\varepsilon(k) \qquad (23)$$

$$D(k) = D(k-1) + \mu_D e(k)\Gamma(k)(\varepsilon(k) - 2\varepsilon(k-1) + \varepsilon(k-2)) \qquad (24)$$

Where term, $\hat{\Gamma}$ comes from Eq. (19), and μ is the fixed learning rate of each adaptive PID parameter. Fig. 3 depicts the block diagram of the resulting network topology based on the PID controller for self-tuning controls WECS's.
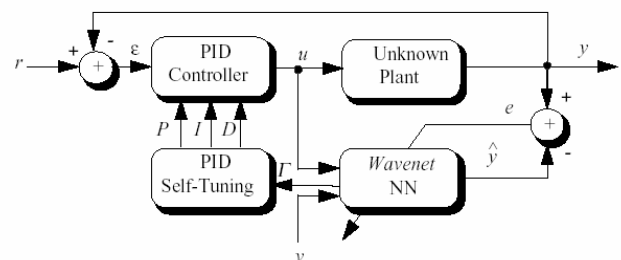

Fig. 3 Closed loop block diagram

World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:2, No:1, 2008

The optimum shaft rotational speed ω_{opt} is obtained, for each wind speed V_w, and used as a reference for the closed loop. Note that wind speed acts also as a perturbation on the turbine's model. Actually, the turbine is linked with the generator's shaft using a gearbox, which imposes an additional transform relation in the model. Dynamics of this gearbox are considered unknown.

IV. SIMULATION RESULTS

A. Approximation of WECS

In this section, it will be shown through simulations RASP1 mother wavelet basis functions perform their learning ability. Using the data from the WECS extracted from [10], the wavenet network with different size and RASP1 mother wavelets is employed to approximate the WECS data. IIR block structure with feed forward coefficients M=3 and feedback coefficients N=3 is also implemented. Moreover, wavelets are local basis functions that provide less interfering than global ones, leading to a noncomplex dependency in the NN parameters. This section will confirm this idea by providing several observations derived from the results of the MATLAB simulations. Assuming the training data are stationary and sufficiently rich, good performance can usually be achieved with a small learning rate. Thus, all learning rate parameters for weights, dilations, translations, IIR feed forward coefficients, and feedback coefficients are fixed at 0.005, 0.025, 0.0250, 0.01, and 0.01, respectively. All initial weights w_k and dilations a_k are set to 0 and 10, respectively. Note that if the dilation parameters are set too wide, they can cause several overlapping partitions and thus cannot be rallied. Setting a_k too narrow may result in longer convergence.

Initial translation parameters b_k are spaced equally apart throughout the training data to provide non-overlapping partitions throughout the neighboring intervals. Finally, the initial IIR coefficients c and d should be set so that system has poles inside the unit circle, thus both are set to 0.1.

The learning epoch will terminate when the desired normalized error of 0.0324 is reached.
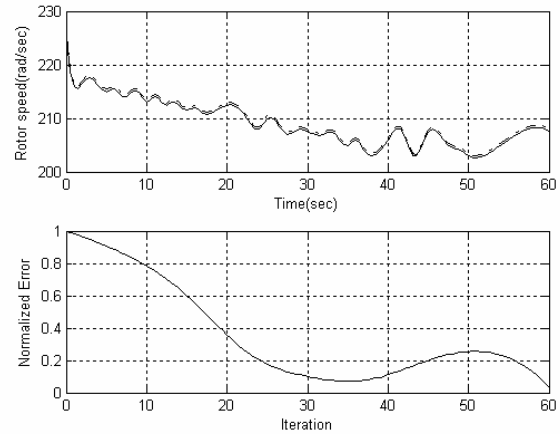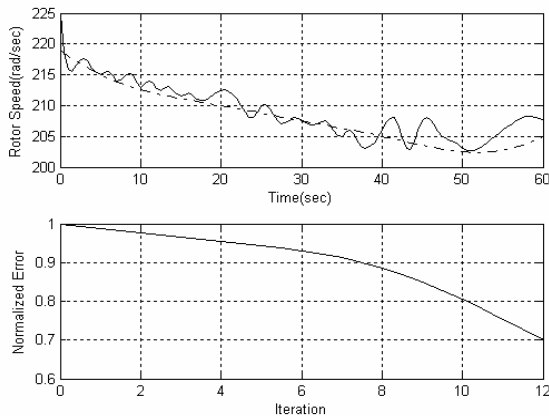

Fig. 4 Wavenet simulations with 36 RASP1 wavelets
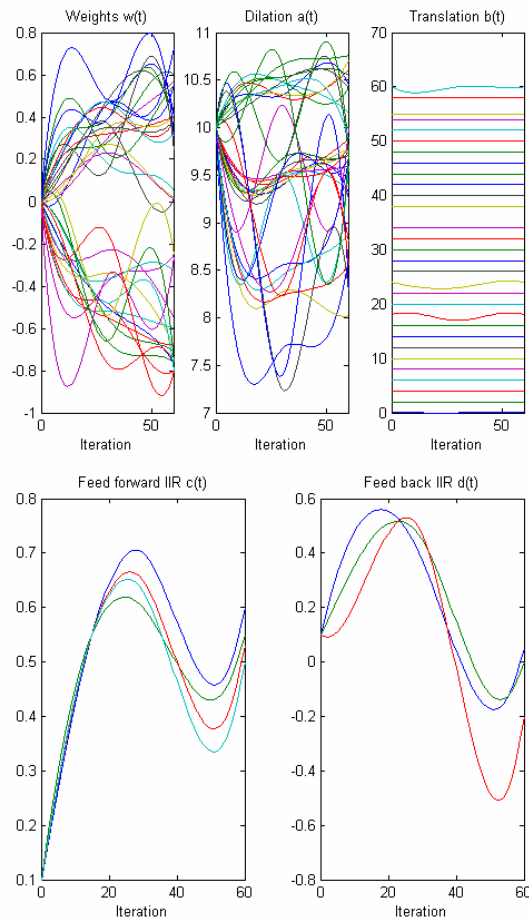Solid: plant output and Dotted: NN output

Fig. 5 Wavenet Parameter Updates with RASP1 Wavelets

Figs 4 and 5 and Table I illustrates the approximation of WECS performance. The results show that *wavenet* employing 36 RASP1 wavelets can reach the error goal of 0.032 in the fastest time among all mother wavelets experimented at 60 iterations. However, again when we oversize the number of wavelets to $K = 60$ and 75, the normalized error starts to oscillate steadily resulting in prolong time consumption to reach the fine error target. From

World Academy of Science, Engineering and Technology
International Journal of Electrical and Computer Engineering
Vol:2, No:1, 2008

Table I, the best number of wavelets to employ in the *wavenet* network for approximation of the WECS model turns out to be 36. Similar to these results have obtained for unknown voice model [8].

TABLE I
NUMBER OF ITERATIONS VS. NUMBER OF RASP1 WAVELETS EMPLOYED

Number of Iterations	Number 0f Wavelets							
	9	15	18	24	36	48	60	75
Error of 0.85	17	14	14	14	12	9	9	9
Error of 0.48	58	35	20	20	18	15	15	12
Error of 0.32	165	73	26	23	21	18	15	15
Error of 0.15	3001	128	53	38	27	24	21	60
Error of 0.05		205	76	48	55	45	42	osc illa te
Error of 0.04		232	110	53	57	84	48	osc illa te
Error of 0.032		310	210	67	60	102	osci llat e	

B. Control

After the identification model is completed, the tracking operation takes command of the neuro process PID control to track the desired set point ω_{opt}. The co-input $v(t)$ is set to 0.95.

In Fig. 6 the results of the WECS control using the proposed self-tuning neuro wavenet controller with 36 RASP1 compare with the results of the WECS control using the combined RBF/supervisor control [6]. In this figure, a step sequence of step-shaped wind gusts is applied to the system. The resulting evolution of the closed loop converges rapidly to the desired optimal rotational speed with simple first-order dynamics. Fig. 7 depicts the turbines developed torque versus rotational speed, for the same input sequence. Superimposed (in dotted line) the turbines characteristic curves are displayed. It can be seen that the torque trajectories of the controlled system converge to points belonging to the maximum torque curve. In Fig. 6 is showed that proposed method is better than RBF method [6] regarding simulation accuracy. The proposed controller can be efficiently implemented on digital signal processors.
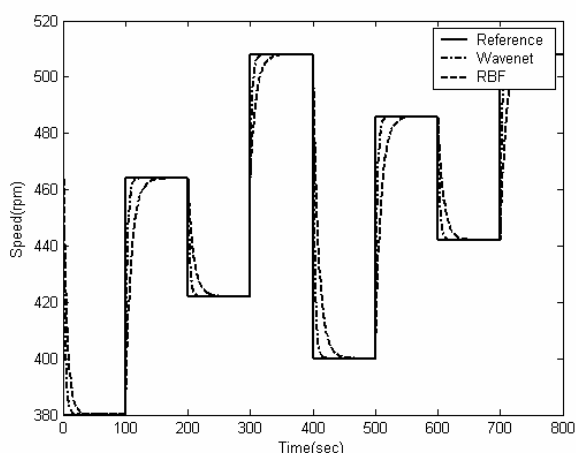

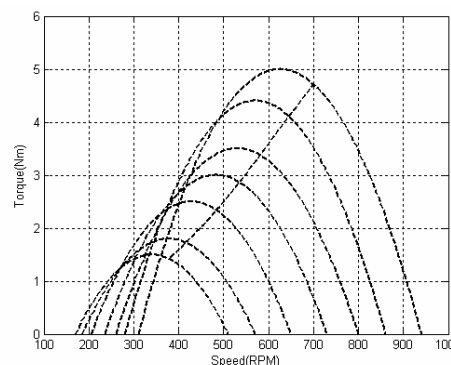Fig. 6 PID Neuro Wavenet Controller Responses to a sequence of wind gusts

Fig. 7 System response on torque/speed coordinates, for the same input sequence of Fig. 6 developed torques (points) converges to the maximal torque curve, ensuring optimal operation

V. CONCLUSION

This paper discussed the application of wavenet networks in the implementation of adaptive controllers for WECS's. The approach used, based on a single layer feed forward neural networks with hidden nodes of adaptive RASP1 wavelet functions PID controller and an infinite impulse response (IIR) recurrent structure , allowed fast convergence to a simple linear dynamic behavior, even in the presence of parameter changes and model uncertainties. The resulting controller showed to be simple enough to be synthesized using signal processors.

REFERENCES

[1] P.Puleston, "Control strategies for wind energy conversion systems", Ph.D. dissertation, Univ. La Plata, Argentina, 1997.
[2] P. Simoes, B. K. Bose, and R. J. Spiege, "Fuzzy logic-based intelligent control of a variable speed cage machine wind generation system,", IEEE Trans. Power Electron., Vol. 12, no. 1, Jan. 1997.
[3] F. D. Kanellos, N. D. Hatziargyriou, "A new control scheme for variable speed wind turbine using neural networks", IEEE Power Engineering Society Winter Meeting, 2002, Vol.1, 27-31Jan.2002.
[4] S. Li, D. C. Wunsch, E. A. O'Hair, "Using neural networks to estimate wind turbine power generation",IEEE Transaction on energy conversion, Vol. 16, No.3, Sept 2001.
[5] S. Haykin, Neural Networks, A Comprehensive Foundation. New York: Macmillan, 1994.
[6] M. A. Mayosky, G. I. E. Cancelo, "Direct adaptive control of wind energy conversion systems using gaussian networks", IEEE Transactions on neural networks, Vol. 10, No. 4, july 1999.
[7] X. Ye, N. K. Loh,"Dynamic system identification using recurrent radial basis function network," Proce. American control conf. , Vol. 3,June 1993.
[8] G. Lekutai, "Adaptive Self-Tuning Neuro Wavelet Network Controllers"; PhD Thesis, Virginia Polytechnic Institute and State Universitym, 1997.
[9] A.U. Levin and K.S. Narendra, "Control of nonlinear dynamical, PII: Obserabiliy, Identification and control," IEEE Trans. On Neural Network,1995
[10] "Data base of wind characteristics", downloaded from www.windata.com