International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

September 2014 | Issue 20 | Volume 6 | Number 3 | Pages 29-37

NONLINEAR MODEL IDENTIFICATION AND ADAPTIVE CONTROL OF VARIABLE SPEED WIND TURBINE USING RECURRENT NEURAL NETWORK

D. Arzaghi Haris [1] M. Sedighizadeh [2]

1. Faculty of Engineering, Saveh Branch, Islamic Azad University, Saveh, Iran, arzaghi_harris@yahoo.com
2. Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran, m_sedighi@sbu.ac.ir

Abstract- The best configuration for generating electricity energy form a variable-speed wind energy conversion system (WECS) is using double-output induction generator (DOIG). Controlling this system in order to optimum performance on maximum extracting power from wind in each speed were attracted the attention of many researchers. This kind of generators use a rectifier and inverter know as static Kramer drive (SKD) and changes on the firing angle of the inverter can control the operation of the generator. Achieving above purpose is difficult because the behavior of this system under classic controller is very time variant and nonlinear and need to an adaptive controller is presented. With regard to high capability of neural network in control subject, in this paper one structure of this kind of networks for controlling wind energy conversion system was proposed. This controller uses recurrent neural network based on approximation of non-linear autoregressive moving average (NARMA) model. Feasibility and effectiveness of controller are demonstrated by simulation results. Different cases, such as applying a distinct disturbance, applying noise to system and Parameters variations and uncertainties of the system in order to study the ability of proposed controllers, were considered.

Keywords: Double-Output Induction Generator, Wind Turbine, Neural Network Controller, Model Identification, Autoregressive Moving Average.

I. INTRODUCTION

Motivated by the high dependence of global economies on fossil fuels and concerns about the environment, increasing attention is being paid to alternative methods of electricity generation [1]. Clean renewable energy sources such as solar and wind, have been developed over recent years. Wind is now on the verge of being truly competitive with conventional sources. The cost, weight, and maintenance needs of mechanical gearing between the wind turbine and the electrical generator pose a serious limitation to the further increase in WECS power ratings [2].

Control plays a very important role in modern WECS. In fact, wind turbine control enables a better use of the turbine capacity as well as the alleviation of aerodynamic and mechanical loads, which reduce the useful life of the installation [1]. 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 [3].

Many authors [4, 5, 6] surveyed fuzzy logic control, neural network (NN) control, expert system control and synthesis intelligent control methods that is used in the stability, speed control system and maximum-power transfer of WECS.

Different non-linearization control ways have used for WECS. One of the best non-linearization control systems for the control of non-linearization system and high uncertainty is the use of adaptive self tuning strategy by use of NN. Mayosky and Cancelo [3] used this idea to control the WECS. They proposed a NN based structure consisting of two combined control actions -a Radial Basis Function (RBF) and a supervisory control network- based self tuning adaptive controller.

Sedighizadeh et al. [7, 8, 9] used the idea of Self tuning control of nonlinear systems using NN adaptive frame wavelets to identify and control the WECS. They suggested an adaptive PI and PID controller using Rational function with Second-order Poles (RASP1) wavenets for wind turbine control. Sedighizadeh et al. [10] also suggested an adaptive controller using Morlet wavelets frames NN for identification and control of WECS. After that, Sedighizadeh et al [11] used the adaptive RBF PID controller based on reinforcement learning presented by WANG Xue-song et al. [12] to control the WECS. Also Sedighizadeh et al suggested an adaptive PID control based on lyapunov to control of WECS in [13].

Valenciaga et al. [14] present a control strategy based on adaptive feedback linearization intended for variable-speed grid-connected WECS. The proposed adaptive control law accomplishes energy capture maximization by tracking the wind speed fluctuations. The main idea of our paper is extracted from Valenciaga's work and the identification and control of WECS has been performed using recurrent neural network.

This paper is organized as follows. Section II derives the model of the system to be controlled. The resulting open-loop system is highly nonlinear. In section III the proposed adaptive controller based on recurrent neural network is introduced. Section IV discusses the application of proposed control strategy in WECS. The complete closed-loop system and simulation results are analyzed in this Section. The robustness of the proposed adaptive controller is evaluated by different cases. Finally, Section V resumes the conclusions.

II. WIND ENERGY CONVERSION SYSTEMS

Since the inception of the wind energy technology, machines of several types and shapes were designed and developed around different parts of the world. WECS are usually found in two schemes: fixed-speed, and variable-speed. Fixed-speed WECS operate with optimum conversion efficiency only at a single wind speed. In order to make a better use of the turbine, variable-speed WECS were subsequently developed [1].

A. Wind Turbine Characteristics

In this section, we present the application of wind turbine. Most of today's commercial machines are horizontal axis wind turbine (HAWT).

Commonly, the output mechanical power and the torque developed by the wind turbine are expressed in terms of non-dimensional power (C_P) and torque (C_T) coefficients as follows [1]:

$$P_t = 0.5\rho\pi R^2 C_P \left(V_\omega\right)^3 \tag{1}$$

$$T_t = 0.5\rho\pi R^3 C_T \left(V_\omega\right)^2 \tag{2}$$

where C_P and C_T satisfy

$$C_P = {C_T}/{\lambda} \tag{3}$$

The two coefficients are given as a nonlinear function of the parameter λ

$$\lambda = {R\omega}/{V_\omega} \tag{4}$$

where is the air density, is the radius of the turbine, V_ω is the wind speed, and ω is the rotational speed. Usually, C_P is approximated as follows,

$$C_P = \beta\lambda + \gamma\lambda^2 + \delta\lambda^3 \tag{5}$$

where β, γ and δ are constructive parameters for a given turbine. Figure 1 depicts typical C_P versus turbine speed curves, with V_ω as a parameter. It can be seen that the maximum value for C_P, i.e. $C_{P\max}$ is constant for a given turbine. 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. Figure 2 shows the torque/speed curves of a typical wind turbine, with V_ω as a parameter. The operation points of maximum power transference are marked on each curve. It can be observed that the maximum C_P (and thus, maximum generated power) and the maximum torque are not obtained at the same speed.

The optimal performance is achieved when the turbine operates at the $C_{P\max}$ condition. This will be the control objective in this paper [3].

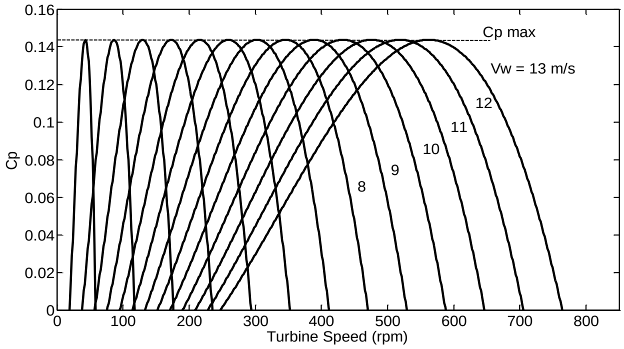

Figure 1. Power coefficient C_P versus turbine speed. Wind speed is the parameter [3]

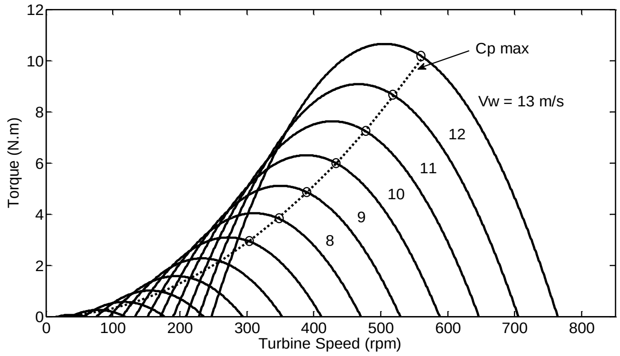

Figure 2. Torque versus shaft speed characteristics of a wind turbine $T_t - \omega$ for different values of wind speed

B. Induction Generators and Slip Power Recovery

There are basically two generator configurations for variable-speed WECS:

- Direct drive synchronous generator
- Double output (wound rotor) induction generator (DOIG)

In the DIOG based system, the stator power is directly fed to the grid. However, the rotor power is partially recovered through an uncontrolled bridge rectifier, a line commutated inverter and a filter which are known as SKD and can change the electrical frequency as desired by the grid. The generator torque, and hence the system speed, can be controlled by modifying the firing angle of the inverter. Typical configuration of such a system is shown in Figure 3.

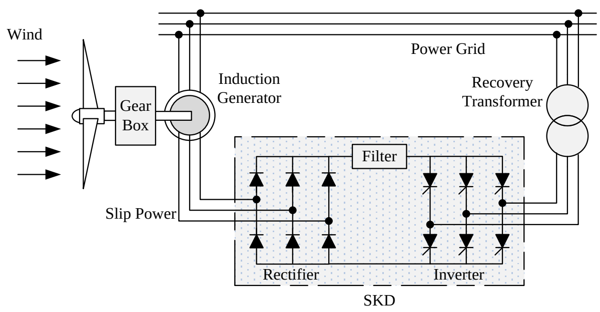

Figure 3. Schematic diagram of the WECS with DFIG

A simplified expression for the torque developed by the generator/Kramer drive combination is:

$$T_g = \frac{3sV_s^2 R_{eq}}{\Omega_m \left[\left(sR_s + R_{eq} \right)^2 + \left(s\Omega_e \left(L_{ls} + L_{lr} \right) \right)^2 \right]} \tag{6}$$

where

$$R_{eq} = \frac{s\left[n_2^2 s R_b + \left(n_1 \left|\cos(\alpha)\right| \right)^2 R_s - n_1 \left|\cos(\alpha)\right| \sqrt{\Gamma} \right]}{\left(\left(n_2 s \right)^2 - \left(n_1 \left|\cos(\alpha)\right| \right)^2 \right)}$$

$$R_b = R_r + 0.55 R_f \tag{7}$$

$$\Gamma = 2n_2^2 R_b s R_s + \left(n_2 s R_s \right)^2 + n_2^2 \left(s\Omega_e \left(L_{ls} + L_{lr} \right) \right)^2 + \left(n_2 R_b \right)^2 - \left[n_1 \left|\cos(\alpha)\right| \left(\Omega_e \left(L_{ls} + L_{lr} \right) \right)^2 \right]$$

where s is the generator slip, V_s the stator voltage, R_r, R_s, R_f the resistance of rotor, stator and filter (dc link), respectively, L_{ls} , L_{lr} the leakage inductance of stator and rotor, Ω_m the mechanical synchronous rotational speed, the synchronous electrical angular frequency, n_1 the transformation ratio between rotor and stator wounds, n_2 turn ratio of the transformer between the SKD output and the AC line and α the firing angle of inverter. (All values referred to the rotor side).

Equation (6) can be simplified, for design purposes, by using a first-order approximation

$$T_g = \frac{3V_s^2}{\Omega_m^2 R_b n_2}\omega - \frac{3V_s^2 \left(n_1 \left|\cos(\alpha)\right| + n_2 \right)}{\Omega_m R_b n_2} = d_1\omega + d_2\cos(\alpha) + d_3 \tag{8}$$

where d_1, d_2 and d_3 are constants.

C. Turbine / Generator Model

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

$$J\omega^{\bullet} = T_t\left(\omega, V_\omega\right) - T_g\left(\omega, \alpha\right) \tag{9}$$

where J is the total moment of inertia. Regarding (2), (3), (5) and (8), system's model become

$$J\omega^{\bullet} = \frac{1}{J}\left[0.5\rho\pi R^3 \left(\beta + \gamma\lambda + \delta\lambda^2 \right) \left(V_\omega \right)^2 - -d_1\omega - d_2\cos(\alpha) - d_3 \right] \tag{10}$$

where λ and depend on ω in a nonlinear way (4). Generator parameters change due to aging and temperature. Therefore using a nonlinear adaptive control strategy is required. This control strategy system aims at placing the turbine in its maximum power generation point, despite the variations in the wind speed and generator's parameters. The turbine torque, T_t for a given V_ω, and the generated torque, $-T_g$, for a given , are sketched in Figure 4.

It should be mentioned that for a given wind speed, the turbine's operational curve and optimum generation point are fixed. According to (9), the intersection of T_t and $-T_g$ curves represents the equilibrium point () of the turbine-generator pair. The control strategy converges the rotational speed, ω, and turbine torque, T_t, to their optimal values by changing the firing angle of the inverter, as the wind speed changes [3].

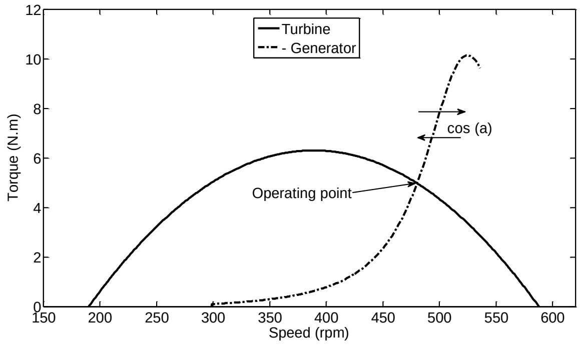

Figure 4. Control strategy proposed. The firing angle is adjusted so that the turbine's operation point settles to the $C_{P\max}$ condition

The designing of system is so that the maximum turbine torque occurs 0.5 to 0.7 of the generator torque peak. Regarding to the generator torque curves in this region T_g is considered as a linear expression [3]. The generated torque curve in optimal point is shown in Figure 4. The standard normal form for expression in (10) can be rewritten as

$$\omega^{\bullet} = f\left(\omega\right) + bu \tag{11}$$

where f f is a nonlinear function of rotational speed, ω, is a constant and is the system input which is the $\cos(\alpha)$.

III. PROPOSED CONTROL STRATEGY

Nowadays, considerable attention has been focused on use of artificial neural network (ANN) on system modeling and control applications. The NN has several key features that make it suitable for controlling nonlinear systems. These features include parallel and distributed processing, and efficient nonlinear mapping between inputs and outputs without an exact system model. Also NNs are characterized by the rapidity of response and robustness, which make them attractive to control WECS [2]. The most successful topologies for this purpose are recurrent neural network. They are important because most of the system to be modeled and controlled are indeed nonlinear dynamic ones and used feedback in these structures lead to performing control function well [15].

There are typically two steps involved when using neural networks for control:

1. System identification
2. Control design

System identification is the procedure that develops models of a dynamic system based on the input and output signals from the system. And in the control design stage, the neural network plant model is used to design (or train) the controller.

The representation of single input single output (SISO) dynamical systems using state equations is currently well known. Let a system Σ be represented by state equations

$$\Sigma: \quad x(k+1) = f\left[x(k), u(k)\right] \qquad y(k) = g\left[x(k)\right] \tag{12}$$

where $\{x(k)\}$, $\{u(k)\}$, and $\{y(k)\}$ are discrete time sequences with $x(k) \in \Re^n$, $u(k) \in \Re$, and $y(k) \in \Re$. The only accessible data are the input u and output y. If the linear system around the equilibrium state is observable, an input-output representation exists which has the form is known as nonlinear autoregressive moving average (NARMA) model:

$$y(k+1) = \phi\big(y(k), y(k-1), \cdots, y(k-n+1), u(k), u(k-1), \cdots, u(k-n+1)\big) \tag{13}$$

i.e. a nonlinear function exists that maps $y(k)$, and $u(k)$, and their past values, onto .

Even assuming that such a model is available (or has been identified using neural networks), determining the control input that results in a desired output is no longer a simple task since the output depends nonlinearly on the input. As a consequence, various approximate methods have been proposed for the determination of the control input [16]. Narendra et al. [16, 17] present two approximate input–output models derived from the NARMA model, in which the control input appears linearly. As mentioned in this paper, designed neural controllers by these approximation models have better performance than neural controllers based on precise NARMA model.

When the system (12) in a neighborhood of the equilibrium state, has a relative degree d (for defining relative degree refer to [17]), it can be shown that the input-output representation of the system is given by [16]:

$$y(k+d) = \bar{\phi}\big(y(k), y(k-1), \cdots, y(k-n+1), u(k), u(k-1), \cdots, u(k-n+1)\big) \tag{14}$$

Equation (14) is for identification of given system and its control is needed.

A. Identification Using Neural Networks

Since the function $\bar{\phi}(\cdot)$ is known to exist in a neighborhood of the equilibrium state, a multilayer perceptron (MLP) or a radial basis function (RBF) network can be used to identify it. If $NN: \Re^{2n} \to \Re$ is a map represented by the neural network, identification model is:

$$\hat{y}(k+d) = NN\big(y(k), y(k-1), \cdots, y(k-n+1), u(k), u(k-1), \cdots, u(k-n+1)\big) \tag{15}$$

where $\hat{y}(k+d)$ is the estimate of $y(k+d)$, and can be used to predict the output at time based on past values of the input and output at instant k. The parameters of the network NN are adjusted using static back propagation so as to minimize the below identification error:

$$e_i(k) = \hat{y}(k) - y(k) \tag{16}$$

B. Control Design

Since the relative degree d exists, the system is necessarily controllable and $\partial\bar{\phi} / \partial u(k) \neq 0$ along the trajectory. Hence, by the implicit function theorem [16]

$$u(k) = \Psi\big(y(k), \cdots, y(k-n+1), y_d(k+d), u(k-1), \cdots, u(k-n+1)\big) \tag{17}$$

where $\Psi: \Re^{2n} \to \Re$ exists. The control problem is consequently to determine (or estimate) Ψ from the measured values of inputs and outputs as well as the given desired output $y_d(k+d)$. The adjustments of the parameters of a neural network used to approximate Ψ. For this purpose, the parameters of a neural network used to approximate Ψ must be adjusted (using some gradient method) to minimize the control error expressed in Equation (18).

$$e_c(k) = y(k) - y_d(k) \tag{18}$$

In [16] for this control aim two approximate models are introduced. The main feature of those models is that the control input $u(k)$ at time k (the instant of interest in the control problem) occurs linearly in the equation relating inputs and outputs.

NARMA-L1 Model:

$$y(k+d) = f_0\left[y(k), y(k-1), \cdots, y(k-n+1)\right] + + \sum_{i=0}^{n-1} g_i\left[y(k), y(k-1), \cdots, y(k-n+1)\right] u(k-i) \tag{19}$$

NARMA-L2 Model:

$$y(k+d) = \bar{f}_0\left[y(k), y(k-1), \cdots, y(k-n+1), u(k-1), \cdots, u(k-n+1)\right] + \bar{g}_0\left[y(k), y(k-1), \cdots, y(k-n+1), u(k-1), \cdots, u(k-n+1)\right] u(k) \tag{20}$$

It is seen that $f_0(\cdot)$ and in the equation describing NARMA-L1 are only functions of the past values of the outputs, and $u(k-1), \cdots, u(k-n+1)$ as well as occur linearly on the right-hand side (RHS) of (19). In contrast to this, NARMA-L2 model is described by only two terms in the RHS of (20) where both $\bar{f}_0(\cdot)$ and $\bar{g}_0(\cdot)$ are function of $y(k), y(k-1), \cdots, y(k-n+1)$ and $u(k-1), \cdots, u(k-n+1)$ [16]. This model is in companion form, where the next controller input is not contained inside the nonlinearity. The advantage of this form is that we can solve for the control input. The proposed control structure in this paper is based on NARMA-L2 model.

In our proposed control strategy, the controller is simply a rearrangement of the neural network plant model, which is trained offline, in batch form. It requires least computations and the only online computation is a forward pass through the neural network controller.

The controller is simply a rearrangement of the neural network plant model, which is trained offline, in batch form. The only online computation is a forward pass through the neural network controller. The drawback of this method is that the plant must either be in companion form, or be capable of approximation by a companion form model.

The neural network controller described in this section is referred to by two different names: feedback linearization control and NARMA-L2 control. It is referred to as feedback linearization when the plant model has a companion form. It is referred to as NARMA-L2 control when the plant model can be approximated by the same form [18].

C. Identification of the NARMA-L2 Model

The first stage of this control architecture discussed in this paper is to train a neural network to represent the forward dynamics of the plant. The error between the neural network output and the WECS(plant) output which is expressed in Equation (16) is used as the neural network training signal. The process is represented by Figure 5.

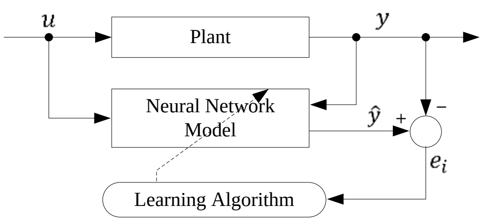

Figure 5. Plant identification

We train a neural network to approximate the nonlinear functions $\bar{f}_0(\cdot)$ and $\bar{g}_0(\cdot)$. Solving the equation (20) form for the control input that causes the system output to follow the desired output $y(k+d)=y_d(k+d)$ we will have

$$u(k)=\frac{y_d(k+d)-\bar{f}_0\left[y(k),\cdots,y(k-n+1),u(k-1),\cdots,u(k-n+1)\right]}{\bar{g}_0\left[y(k),\cdots,y(k-n+1),u(k-1),\cdots,u(k-n+1)\right]} \quad (21)$$

Using this equation directly can cause realization problems, because you must determine the control input $u(k)$ based on the output at the same time, $y(k)$. So, instead, use the model

$$\begin{aligned} y(k+d) = {} & \bar{f}_0\left[y(k),y(k-1),\cdots,y(k-n+1),\right. \\ & \left. u(k),u(k-1),\cdots,u(k-n+1)\right]+ \\ & +\bar{g}_0\left[y(k),y(k-1),\cdots,y(k-n+1),\right. \\ & \left. u(k),\cdots,u(k-n+1)\right]u(k+1) \end{aligned} \quad (22)$$

where $d \geq 2$. The structure of the neural network plant model is given in Figure 6, where the blocks labeled TDL are tapped delay lines that store previous values of the input signal. This structure is known as Recurrent or dynamic neural networks. Notice that we have separate sub-networks to represent the functions $\bar{f}_0(\cdot)$ and $\bar{g}_0(\cdot)$.

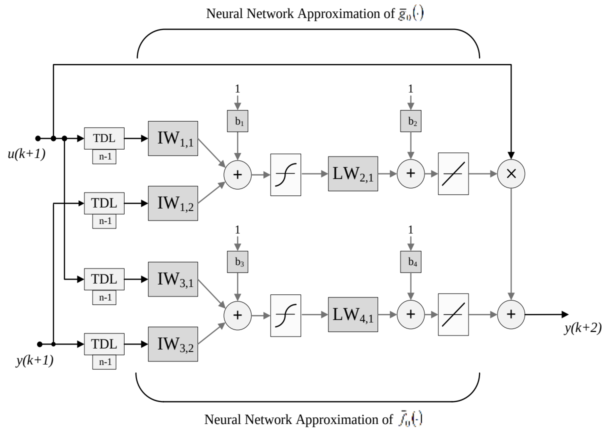

Figure 6. NARMA-L2 plant model

D. The NARMA-L2 Controller

Using the NARMA-L2 model and equation (22), we can obtain the input of the controller

$$u(k+1)=\frac{y_d(k+d)-\bar{f}_0\left[y(k),\cdots,y(k-n+1),u(k),\cdots,u(k-n+1)\right]}{\bar{g}_0\left[y(k),\cdots,y(k-n+1),u(k),\cdots,u(k-n+1)\right]} \quad (23)$$

which is realizable for $d \geq 2$. This controller can be implemented with the previously identified NARMA-L2 plant model, as depicted in Figure 7.

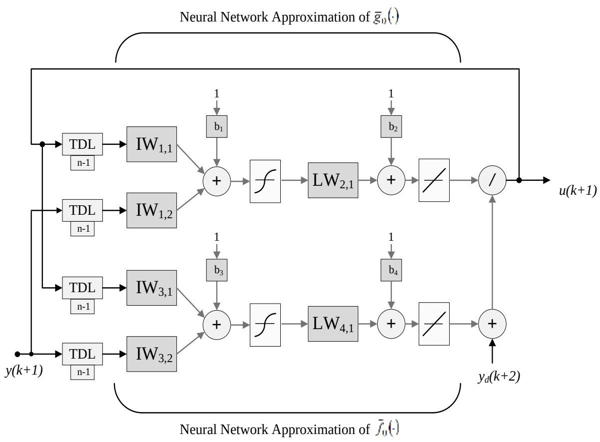

Figure 7. Implementation of NARMA-L2 Controller

The neuro controller for NARMA-L2 control WECS is provided in Figure 8, in which the input signal of system is cosine of firing angle of the inverter and its output is the speed of turbine shaft.

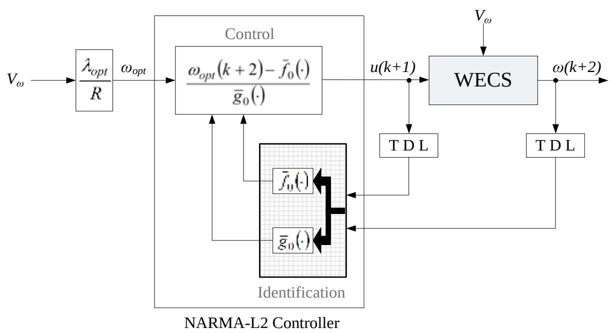

Figure 8. Closed loop block diagram

The optimum shaft rotational speed ω_{opt} is obtained for each wind speed V_{ω}, and used as a reference for the close loop control of WECS. In reality, yields the speed in which the extracted power from turbine is maximum. Note that wind speed also acts as a perturbation on the turbine's model. Actually, the turbine is coupled with the generator's shaft using a gearbox, which imposes an additional unknown dynamic to the model.

Each subnetwork that is used for approximation of $\bar{f}_0(\cdot)$ and $\bar{g}_0(\cdot)$ has a two layers structure. Activation functions of hidden layers and output layers are hyperbolic tangent sigmoid (tansig) and Purelin respectively. It is shown in Figure 6. In addition, the network uses the Levenberg- Marquardt back propagation algorithm for training. Two sets of inputs enter to the neural network model of system (identification block in Figure 8): delayed values of the plant output, and delayed values of the controller output. The controller is obtained directly with a simple equation from identified model. The controller structure distinguishes with modification of delayed values in input layer and number of neurons in hidden layer.

IV. SIMULATION RESULTS

A. Identification of WECS

In this section, the proposed controller is employed to develop a NN model of the plant. The characteristics of the turbine/generator pair used for the simulations in this paper are summarized in [3], but they are considered unknown for the controller.

To modeling stage requires the acquisition of process inputs-outputs data. For the different WECS's modes to be activated, we will apply a signal rich in frequencies: a pseudo-random sequence around the requested system output.

The input vectors and target vectors are randomly divided into two sets as follows:

- 75% of them are subject to use for training of neural network controller.
- The reminded 25% are utilized for network testing that capability of network is evaluated.

The desire multilayer structure of network which is used for identification and control of the WECS has been obtained by trial and error method. Number of considered training sample are 32000. The best configuration is when delayed values of the plant output are 4 and delayed values of the controller output are considered 3. In each hidden layer, 17 neurons are placed. So, each sub-network has a structure like 6-17. Initial values of weights and biases are supposed zero.

The change in the performance error during the NN learning process is shown in Figure 9. To evaluate accuracy of identified neural model of WECS, a linear regression is applied to the network outputs and the corresponding targets. The Fig. 10 shows the results. This figure shows the actual output tracks the reference output very well for training and testing, and the R-value (Correlation Coefficients) is over 0.99 for the total response.

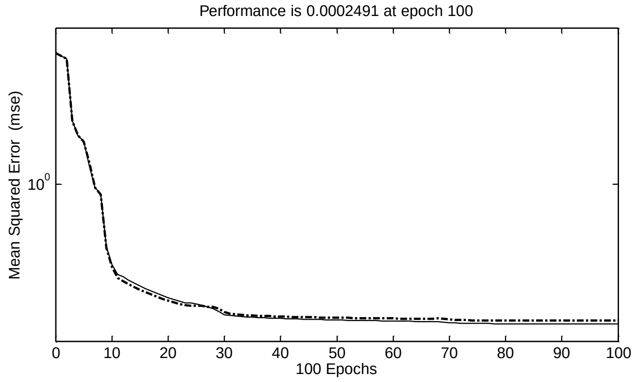

Figure 9. Change in the performance error during the NN learning process (Solid: train and Dotted: test)

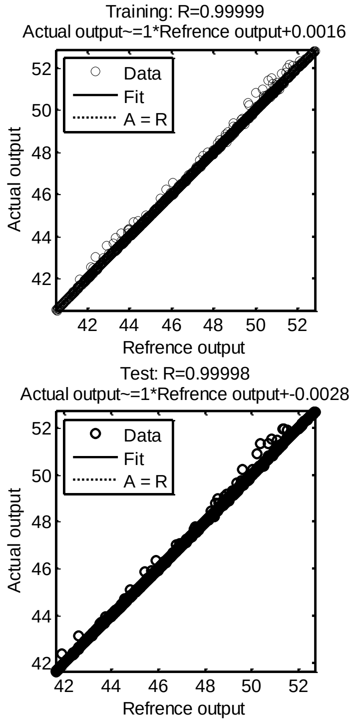

Figure 10. Linear regression between the network outputs and the corresponding references (values are in m/s)

B. Control

When WECS was identified well, neural network controller (control block in Fig. 8) implement for tracking of desired set point. In addition to main duty of controller which is tracking of desired signal (in here is optimum wind speed), it should have some characterizations. For instance it should reject instinct disturbance, should resist in front of noisy system, also it should perform its functions properly if parameters of identified system became uncertain or changed a little. So this stage has been done for three different cases to investigate the quality of proposed controllers.

- *Case 1*: a major disturbance in wind turbine speed is applied at 570 seconds.
- *Case 2*: a random Gaussian noise with normal distribution an variance 0.001 adds to R_{eq} which is a function of input $\cos(\alpha)$.
- *Case 3*: according to Equation (10)

$$\omega(k+1) = F\left(m\cos(\alpha)\right) \tag{24}$$

where $F(\cdot)$ is a nonlinear function of $\cos(\alpha)$, and is a scalar value. During the learning of neural system model step (identification phase), m m value equal to1. Now for control phase it has been supposed that a parameter is varied and its value consider equal to 1.3.

- *Case 1*: The simulation results are displayed in Figure 11. In this figure, a pseudoaleatory 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. In addition, it can be shown that the applied disturbance rejects quickly and appropriate performance of controller leads to the closed loop system goes to its normal behavior in less than 0.2 seconds. Variations of control signal, $\cos(\alpha)$, during control process are demonstrated in Figure 12.

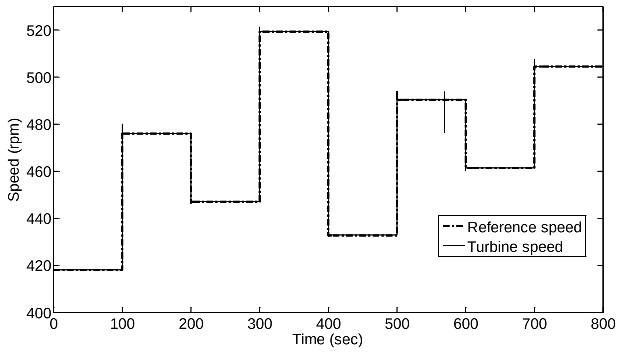

Figure 11. Closed loop system response to a pseudoaleatory sequence of wind gusts in case 1

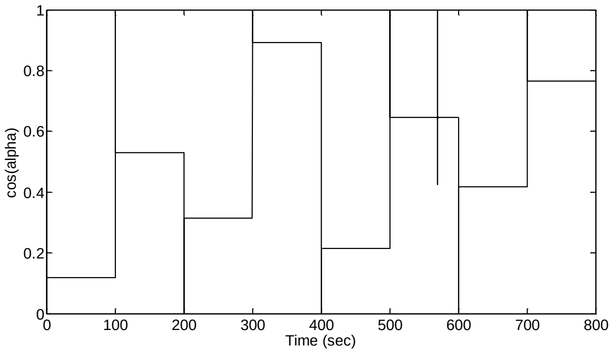

Figure 12. Variations of control signal, $\cos(\alpha)$ in case 1

- *Case 2*: Figure 13 shows simulation results in this case. Considering applied noise in system the controller can guarantee stability of system. Variations of control signal are demonstrated in Figure 14.

- *Case 3*: If some parameters of a nonlinear WECS changed, many controllers can not control them well and desired signal tracking may be unacceptable. The simulation results have been shown in Figures 15 and 16. As we can observe, in this case with regarding to adaptive characteristic of controller, the rotational speed of turbine shaft signal follow the referent signal speed as well and the controlled system is robust against parameter variations and uncertainties.

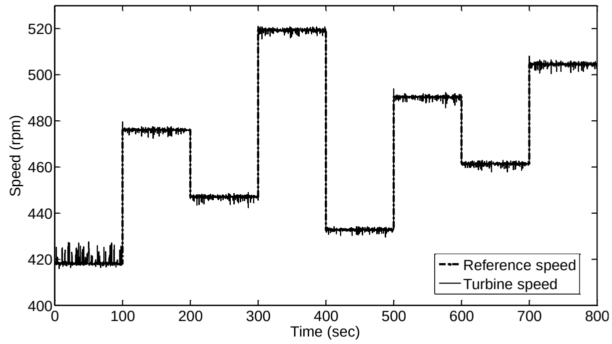

Figure 13. Closed loop system response to a pseudoaleatory sequence of wind gusts in case 2

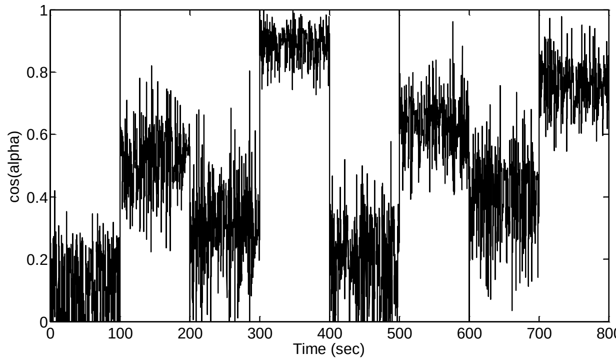

Figure 14. Variations of control signal, $\cos(\alpha)$ in case 2

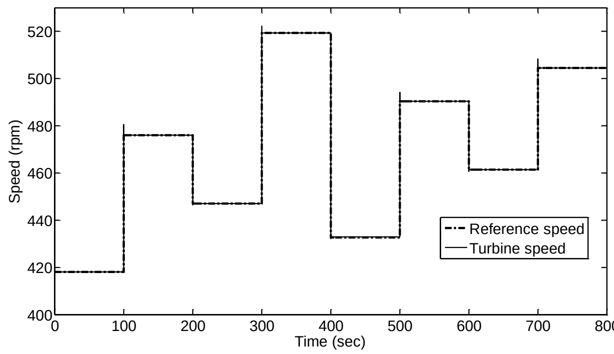

Figure 15. Closed loop system response to a pseudoaleatory sequence of wind gusts in case 3

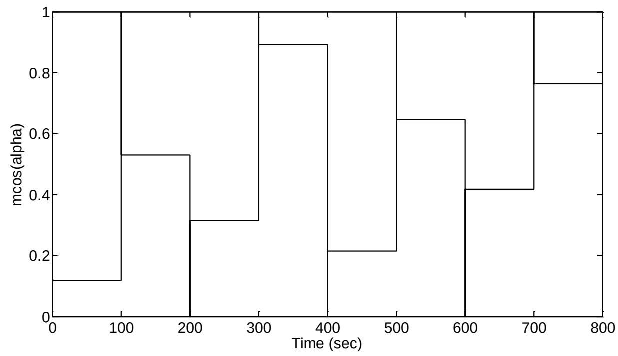

Figure 16. Variations of control signal, $m\cos(\alpha)$ in case 3

Another figure that could show us the way of desired performance of presented controller architecture for extracting maximum power of WECS, is the turbine torque curves versus rotational speed of one, for given wind entrance. This curve has been shown in Figure 17, in which the characteristic of turbine in various wind speed also are added. It is obvious that the path of torque controlled system converge toward points that maximum power is extracted form wind.

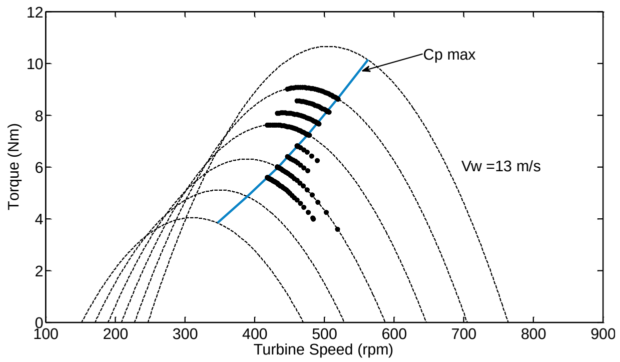

Figure 17. System response on torque/speed coordinates, for the same input sequence of Figure 11. Developed torque (points) converges to the maximal torque curve, ensuring optimal operation

V. CONCLUSIONS

A control strategy to optimize power generation of variable speed grid-connected WECS was presented. This paper discussed the application of NN in the implementation of adaptive controllers for WECS. The utilized approach, based on a recurrent neural network, allowed fast convergence to a nonlinear dynamic behavior.

The effectiveness of the control has been demonstrated through the use of computer simulation to investigate the quality of proposed controller different cases were considered and was shown that presented controller is robust against major instinct disturbance of system, noisy condition and uncertainties and changes in parameters and it could do the tracking very well.

Finally, it is important to remark that even though calculations were made for a particular variable speed WECS, idea behind the control strategy developed in this paper is general and can be readily extended to other systems.

ACKNOWLEDGMENT

The authors were supported in part by a research grant from Saveh Branch, Islamic Azad University, Saveh, Iran.

REFERENCES

[1] F.D. Bianchi, H. De Battista, R.J. Mantz, "Wind Turbine Control Systems", Springer-Verlag London Limited, 2007.

[2] M.N. Eskander, "Neural Network Controller for a Permanent Magnet Generator Applied in a Wind Energy Conversion System", Technical Note, Renewable Energy, Vol. 26, No. 3, pp. 463-477, 2002.

[3] M.A. Mayosky, G.I.E. Cancelo, "Direct Adaptive Control of Wind Energy Conversion Systems Using Gaussian Networks", IEEE Trans. Neural Networks, Vol. 10, No. 4, pp. 898-906, July 1999.

[4] A. Hajebrahimi, R. Moradi, M. Rashidinejad, A. Abdollahi ,"Impact of Wind Penetration to Connect the Large Scale Distant Wind Farm into the Grid in Probabilistic Multi Objective Transmission Expansion Planning", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 18, Vol. 6, No. 1, pp. 82-88, March 2014.

[5] J. Sahebkar Farkhani, H.R. Najafi, "Sensitivity Analysis of Nonlinear of Self Excited Induction Generator (SEIG) in Wind Turbine", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 18, Vol. 6, No. 1, pp. 101-107, March 2014.

[6] R.O. Kyoungsoo, Ch. Han-Ho, "Application of Neural Network Controller for Maximum Power Extraction of a Grid-Connected Wind Turbine System", Electr. Eng. (Archiv Elektrotech), Vol. 88, No. 1, pp. 45-53, 2005.

[7] M. Kalantar, M. Sedighizadeh, "Adaptive Self Tuning Control of Wind Energy Conversion Systems Using Morlet Mother Wavelet Basis Functions Networks", 12th Mediterranean IEEE Conference on Control and Automation MED'04, Kusadasi, Turkey, 2004.

[8] M. Sedighizadeh, M. Kalantar, "Adaptive PID Control of Wind Energy Conversion Systems Using RASP1 Mother Wavelet Basis Function Networks", IEEE TENCON'2004, Chiang Mai, 2004.

[9] M. Sedighizadeh, et al., "Nonlinear Model Identification and Control of Wind Turbine Using Wavenets", IEEE Conference on Control Applications, Toronto, Canada, pp. 1057-1062, 2005.

[10] M. Sedighizadeh, A. Rezazadeh, "Self Tuning Control of Wind Turbine Using Neural Network Identifier," Electr. Eng. (Archiv Elektrotech), Vol. 90, No. 7, pp. 479-491, Sept. 2008.

[11] M. Sedighizadeh, A. Rezazadeh, "Adaptive PID Controller Based on Reinforcement Learning for Wind Turbine Control", World Academy of Science, Engineering and Technology (CESSE 2008), Cairo, Egypt, Vol. 27, pp. 257-262, Feb. 2008.

[12] X.S. Wang, Y.H. Cheng, W. Sun, "A Proposal of Adaptive PID Controller Based on Reinforcement Learning", J. China Uni. Mining & Technology, Vol. 17, No. 1, pp. 0040-0044, 2007.

[13] M. Sedighizadeh, A. Rezazadeh, M. Khatibi, "A Self-tuning PID Control for a Wind Energy Conversion System Based on the Lyapunov Approach", 43rd International Universities Power Engineering Conference (UPEC), 2008.

[14] F. Valenciaga, P.F. Puleston, P.E. Battaiotto, R.J. Mantzt, "An Adaptive Feedback Linearization Strategy for Variable Speed Wind Energy Conversion Systems", International Journal of Energy Research, Vol. 24, pp. 151-161, 2000.

[15] A.S. Poznyak, E.N. Sanchez, W. Yu, "Differential Neural Networks for Robust Nonlinear Control", World Scientific Publishing Co. Pre. Ltd., 2001.

[16] K.S. Narendra, S. Mukhopadhyay, "Adaptive Control Using Neural Networks and Approximate Models," IEEE Trans. Neural Networks, Vol. 8, No. 3, May 1997.

[17] K.S. Narendra, S. Mukhopadhyay, "Adaptive Control Using Neural Networks and Approximate Models", American Control Conference, Seattle, Washington, USA, June 1996.

[18] MATLAB 7, Mathematics, Mathworks Inc.

BIOGRAPHIES

Davood Arzaghi Haris received the B.Sc. degree in Electronic Engineering from Central Tehran Branch, Islamic Azad University, Tehran, Iran and the M.Sc. degree in Electronic Engineering from Urmia University, Urmia, Iran, in 1995 and 1997, respectively. Currently, he is a Lecturer in Faculty of Engineering, Saveh Branch, Islamic Azad University, Saveh, Iran. His research interests are nonlinear systems control and modeling, artificial intelligence, application of optimization in power systems.

Mostafa Sedighizadeh received the B.Sc. degree in Electrical Engineering from Shahid Chamran University, Ahvaz, Iran in 1996, and the M.Sc. and Ph.D. degrees in Electrical Engineering from Iran University of Science and Technology, Tehran, Iran, in 1998 and 2004, respectively. From 2000 to 2007, he was with Power System Studies Group of Moshanir Company, Tehran, Iran. Currently, he is an Assistant Professor in Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran. His research interests are power system control and modeling, FACTS devices, artificial intelligence, application of optimization in power systems and distributed generation.