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A NEW METHODOLOGY TO THE CONTROL PROBLEM OF HORIZONTAL AXIS WIND POWER PLANTS USING ADAPTIVE NEURAL NETWORK

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Abstract: The main goal of this study is to afford an involvement to the control problem of horizontal axis wind power plants by means of neural network approach. The current paper is a part of a research plan to study the dynamics and control of horizontal axis wind turbines. This work presents a novel methodology to control wind power plants. It makes use of an adaptive neural networks self-tuning control system of medium scale wind turbine system, through different operating conditions. The planned control system consists of neural networks forward and inverse identifiers, which are used to model their dynamics, and to adapt neural controller parameters. A reference model is used to enhance the training course and neural controller which is used to produce control signal to the pitch angle actuator. The planned control system carry out high-quality performance which reveal that the proposed control system is in fact an innovative contribution in the control field of horizontal axis wind turbine power generation systems judge against with previous works. *Copyright © 2002 IFAC*

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1. INTRODUCTION

The development of renewable natural energy has attracted considerable interest in recent years primarily due to concern about environment pollution caused by the burning of fossils, and its continually diminishing reserves (Xing-Fang, *et al.*, 2004). Wind turbine generator system provides an environmentally friendly, competitive and socially beneficial means of electricity generation.

Much attention has been paid in recent times to the generation of clean energy. These natural sources of energy need to have no by-products associated with their operation (Moor and Beukes, 2004). The most special feature about wind turbines is the fact that, unlike other power generation systems, the power inflow rate is not controllable (Malinga, 2001). In most generation systems, the fuel flow rate, or the amount of energy, applied to the generator controls the output voltage and frequency. The fact that one has no control over the energy source input, the unpredictability of wind and the varying power demand are more than enough to justify the need for a control system. This will regulate the parameters of the wind energy conversion system that need to be controlled for matched operation of the wind turbine.

2. WIND TURBINE CHARACTERISTICS

The kinetic energy, U of a parcel of air of mass m flowing at upstream speed u in the axial direction (x-direction) of the wind turbine is given by:

$$U = \frac{1}{2} m u^2 = \frac{1}{2} (\rho A x) u^2 \tag{1}$$

Where, A is the cross–sectional (swept) area of the wind turbine in square meters, ρ is the air density in kg/m^3, and x is the thickness of the wind parcel in meters.

The power in the wind P_w, is the time derivative of the kinetic energy and is given in equation (2), which represents the total power available for extraction.

$$P_w = \frac{1}{2} \rho A u^3 \tag{2}$$

As the wind passes over the turbine, the wind will lose power equal to the power extracted by the turbine. The extracted power is usually expressed in terms of the wind turbine swept area A, because the upstream cross-sectional area is not physically measurable as the cross-sectional area of the wind turbine.

$$P_{m,ideal} = \frac{1}{2}\rho\left[\frac{8}{9}\left(\frac{2}{3}A_2\right)u_1^3\right] = \frac{16}{27}\left(\frac{1}{2}\rho A_2 u_1^3\right) = 0.59P_w \quad (3)$$

The factor 16/27 = 0.59 is called Betz coefficient. It shows that an actual turbine cannot extract more than 59 percent of the total power in an undistributed tube of air of the same area (the cross-sectional area equal to the wind turbine swept area).
The fraction of power P_m extracted from the available power in the wind by practical turbines is expressed by the coefficient of performance C_p. The actual mechanical power extracted can be written as:

$$P_m = C_p\left(\frac{1}{2}\rho A u^3\right) = C_p P_w \quad (4)$$

The value of C_p is highly non-linear and varies with the wind speed, the rotational speed of the turbine, and the turbine blade parameters such as pitch angle. The tip speed ratio λ, is defined as the ratio between the rectilinear speed of the turbine tip, $\omega_t R$, and the wind speed u as given in equation (5).

$$\lambda = \frac{\omega_t R}{u} \quad (5)$$

The torque coefficient C_t, also is a highly non-linear function of tip-speed ratio λ and blade pitch angleβ. The torque coefficient C_t, is related to the power coefficient C_p, through the following relation.

$$C_p(\lambda,\beta) = \lambda C_t(\lambda,\beta) \quad (6)$$

Manipulation of the torque coefficient using λ and β will result in manipulation of the power produced by the turbine. The wind turbine mechanical power P_m, is equal to the product of the aerodynamic torque T_A, and the rotational speed.

$$P_m = T_A \omega_m \quad (7)$$

The aerodynamic torque T_A is represented by eq. (8).

$$T_A = \frac{1}{2}\rho A R C_t(\lambda,\beta)u^2 \quad (8)$$

By varying the pitch angle, the aerodynamic torque input to the rotor is altered and hence the output power.

3. WIND TURBINE MODELING

A mathematical model is derived for a horizontal axis medium scale 300kw two-bladed grid-connected up-wind constant-speed full-span, pitch regulated wind turbine, which is dynamically representative of commercial machines of its class. The major components of interest in a wind turbine being controlled are the turbine itself, the drive-train, the generator, power transducer, and the pitch angle actuator. A general block diagram representation of the system dynamics is depicted in Figure 1.

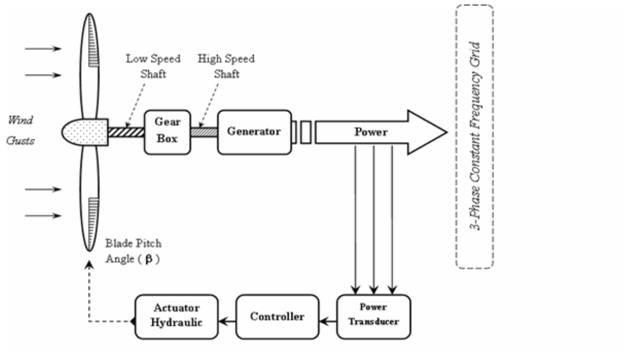

Figure 1.: General Wind Turbine Control Loop

3.1 Turbine Plant Model

The aerodynamic behaviours of the wind turbine is highly non-linear and strongly dependent on wind speed. One difficulty is that the system is non-linear (Mattson, 1984). This is caused by the aerodynamic driving torque. Both the orientation of the turbine rotor (the yaw control) and the pitch angle of the blades influence the driving aero dynamical torque. The important nonlinearities are from the pitch angle, the wind speed and turbine speed to drive aero dynamical torque. The turbine itself can be represented by the equation of motion given in equation (9).

$$J_T \dot{\omega}_t = T_A - T_L \quad (9)$$

where, J_T is the combined moment of inertia of the rotor gear, and both the low-speed and high speed shafts, ω_t is the turbine angular velocity, T_A is the aerodynamic driving torque, and T_L is the load torque, which is the minimum mechanical torque required to turn the generator, and is assumed constant value derived from the turbine plant physical properties.
The non-linear aerodynamic torque can be linearized around an operating point. Assuming $T_A|_{OP} = T_L|_{OP}$, linearization of the equation of motion results in the following:

$$\Delta T = \left.\frac{\partial T}{\partial u}\right|_{OP}\Delta u + \left.\frac{\partial T}{\partial \beta}\right|_{OP}\Delta\beta \quad (10)$$

Simplifying this equation yields:

$$\Delta T = \alpha\Delta u + \delta\Delta\beta \quad (11)$$

Where, ΔT, Δu and $\Delta\beta$ represent deviations from the chosen operating point T_{OP}, u_{OP} and β_{OP}. These deviations are given in the following equations.
$\Delta T = T - T_{OP}$, $\Delta u = u - u_{OP}$, $\Delta\beta = \beta - \beta_{OP}$

The parameters α and δ represent the wind turbine dynamics which are partial derivatives of the aerodynamic torque with respect to the wind speed and pitch angle respectively. They are the rates of change of aerodynamic torque with pitch angle and wind speed, respectively, at the operating point about which the system is linearized. These linearization constants (gains) are essentially a steady state representation of the rather complex aerodynamics of the rotor and as such have a considerable uncertainty which the control system must cope. α and δ change rapidly, by an order of magnitude or more as the wind speed varies.

$$\alpha = \frac{\partial T}{\partial u} = \frac{1}{2}\rho A R u_{OP}\left[2C_t\big|_{OP} - \lambda\big|_{OP}\frac{\partial C_t}{\partial \lambda}\bigg|_{OP}\right] \qquad (12)$$

$$\delta = \frac{\partial T}{\partial \beta} = \frac{1}{2}\rho A R u^2\left[\frac{\partial C_t}{\partial \beta}\right]_{OP} \qquad (13)$$

The transfer function of the turbine plant is then as the following expression:

$$G_P = \frac{\Delta T(s)}{\alpha \Delta u(s) + \delta \Delta \beta(s)} \qquad (14)$$

A block diagram of the linear turbine plant in s-domain is depicted in Figure 2.

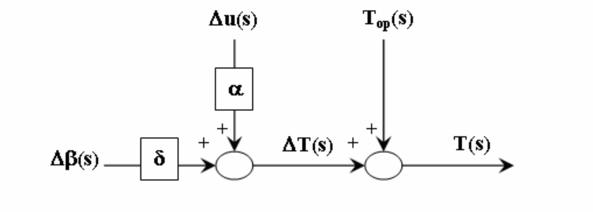

Figure 2 : Block Diagram of the Linear Turbine Plant Model

The uncertainty of the system comes from α and δ which are functions of the wind speed and pitch angle respectively, and they change rapidly and non-linearly.

3.2 Drive-Train and Generator Dynamic

The drive-train converts the input aerodynamic torque on the rotor into the torque on the low-speed shaft which is scaled down through the gearbox and then induces a torque on the high-speed shaft. The model order is determined by the number of rotating masses (Novak *et al.*, 1995). Usually, the two-mass analysis is sufficient, and is used to determine the drive-train dynamics. The drive-train can be represented by the following equations.

$$T_A - T = J_T \dot{\omega}_t \qquad (15)$$

$$T - T_g = J_G \dot{\omega}_g \qquad (16)$$

$$T = T_S + T_D = K_S \int (\omega_t - \omega_g)\,dt + B_S(\omega_t - \omega_g) \qquad (17)$$

Where, T_A is the aerodynamic torque, T is the shaft torque, T_g is the generator torque, K_S is the shaft stiffness, and B_S is the shaft damping. The physical parameters K_S and B_S can be obtained from the manufacturer of the wind turbine.
A three-phase self-exciting induction generator is used for the purpose of this work. The generator is connected directly to the grid which acts like an infinite load. The mechanical and the electrical dynamics of the generator are well represented and modelled. The combined dynamics of the drive-train and the generator is called power-train. As proposed by (Leith and Leithead, 1997), the combined dynamics of the drive-train, generator, and power transducer, are essentially linear and, together, are modelled by the following transfer function.

$$G(s) = \frac{46460.9}{s^5 + 81.27s^4 + 3683.9s^3 + 120773.6s^2 + 147450.4s + 36857450} \qquad (18)$$

This linear transfer function describes the dynamics of the wind turbine in S-domain. The aerodynamic T_A is the input to this transfer function and the output is the power output of the generator measured by a power transducer.

$$G_D(s) = \frac{P_e(s)}{T_A(s)} \qquad (19)$$

The complete power-train dynamics including the generator electrical dynamics are well represented by a fourth-order system.

3.3 Power Transducer Model

A power transducer is used to measure the power output of the generator and feed the controller with measured values after conversion. For the chosen wind turbine, the power transducer can be modelled by a first-order transfer function.

$$G_T(s) = \frac{50}{s + 50} \qquad (20)$$

The time constant of the transducer equal to 20 msec.

3.4 Actuator Model

The pitch actuator consists of a mechanical and electrical system which is used to turn the blades of the wind turbine along their longitudinal axis. For chosen medium scale wind turbine, the actuator position is physically constrained to the range [-2, 60] degrees and the velocity to the range [-10, 10] degrees/second. Since the pitch angle demand is constrained to the range [0, 45] degrees. The former constraint can be neglected and the actuator dynamics can be modelled as a first-order system.

$$G_A(s) = \frac{20.7}{s + 20.7} \qquad (21)$$

By activating the pitch actuator, the aerodynamic torque input to the rotor is altered and hence the output power.

3.5 Complete System Model

A block diagram of the overall system model is illustrated in Figure 3. The complete model describes the dynamics and operating of the wind turbine.

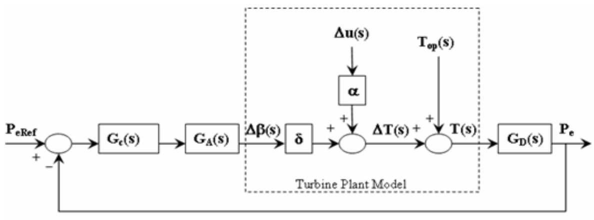

Figure 3: Block Diagram of Overall System Model

Where G_A is the actuator transfer function given in equation (21), G_D is the combined power-train (drive-train and generator) and power transducer transfer function which is given in equation (18), G_c is the controller transfer function, α and δ are the linearization coefficients derived in equations (12) and (13) respectively. The overall system dynamics are modelled for a medium-scale 300kw wind turbine. The wind turbine characteristics are given in reference (Khudair, 2005).

3.6 Wind Speed Profile

The power generated by the wind changes rapidly because the continuous fluctuations of wind speed and direction. From geographic point of view, the power output of each turbine depends on its geographic location on a wind farm and is normally different. The industry standard is to relate the turbine power to the hub-height wind velocity (Li, 2003). In this work, a hub-height wind speed profile is used for system simulation as shown in Figure 4. This profile is generated by computer simulation with 30 second period mean velocity of one per-units (11 mps) and the root mean square of fluctuating component of 0.3 (p.u.). The wind speed profile may seem to be very severe compared with those at practical turbine sites.

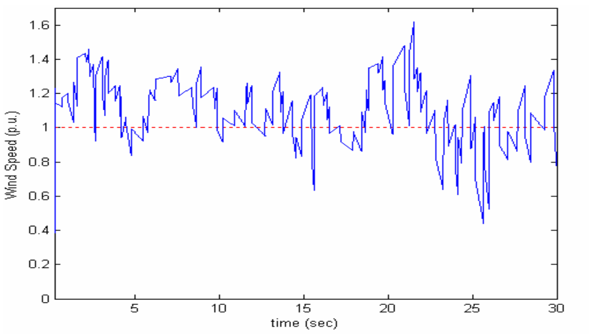

Figure 4: Hub-Height Wind Speed Profile

4. UNCONTROLLED SYSTEM RESPONSE

By applying the wind speed profile given in the previous section with chosen operating point of 13 mps which holds the magnitudes of α and δ equal 2.609665428 per-units and -1.120310916 per-units, respectively, yields Figure 5 which represents the system torque time response.

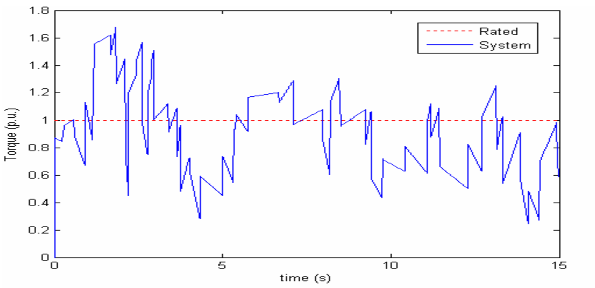

Figure 5: System Torque Response to a Real Wind Speed

5. CONTROL SYSTEM DESIGN

In this work, neural network adaptive self-tuning control system is proposed. The neural network self-tuning control appeared as a result of the dissatisfaction with the ability of the available control system design methods to deal effectively with process control application (Khudair, 2005). After a large number of trial runs, the final architecture proposed of the control system is shown in Figure 6.

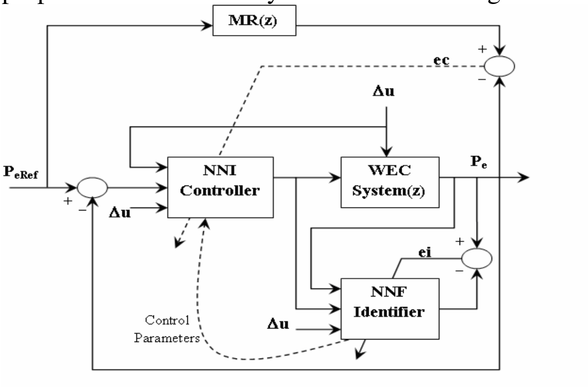

Figure 6: Neural Network Self-Tuning Control Architecture

The key characteristic of this control design approach is the inclusion of plant model and a chosen desired model within the control structure. One of the distinctive features of the proposed control architecture (Phauh, *et al.*, 2003) is to give an efficient method for calculating the derivative of the system output with respect to the input by using one identified parameter in the linearized model and the internal variables of the neural network, which enables to perform the back-propagation algorithm very efficiently. For the operation of the control system, three operating points are chosen for the purpose of the control system designed of this work. The operating points are at the 11, 13, and 15 mps of wind speeds respectively. The design of the neural network self-tuning control system involves three steps. First is developing a neural network inverse identifier which is then configured as a series inverse controller. The second is developing a neural network forward identifier which is used to estimate the Jacobian of the system. Final step involves around choosing an appropriate model which is referred as a reference model. Plant identifiers should be off-line trained first with a data set sufficiently rich to allow plant identification and then both the neuro-controller and the plant forward identifier are on-line trained.

5.1 Inverse Identification

We have used a feed forward neural network with series-parallel identification structure which is more efficient than parallel to track the desired output. The chosen network consists of three-layers, input, hidden, and output layer. The number of neurons in the input and the hidden layer has been experimentally decided to be three in the input layer and fifteen in the hidden layer. A hyperbolic-tangent activation functions are used. After high number of training epochs of about 15000 epochs, the neural network learned the inverse of the plant. Each epoch performs 1500 samples of the chosen period (15 sec), where the sampling time is equal to 0.01 second. Figures 7 and 8 show the training performance and the inverse identification of the system, respectively. The performance error for 15000 epochs is equal to about 1.02854×10^{-13}. After 15000 epochs the error decreases lightly.

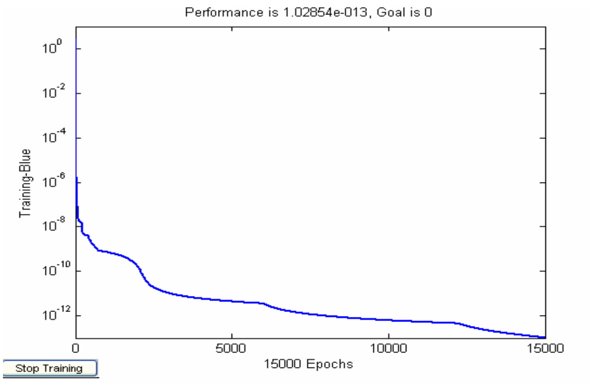

Figure 7: Inverse Identification Training Performance

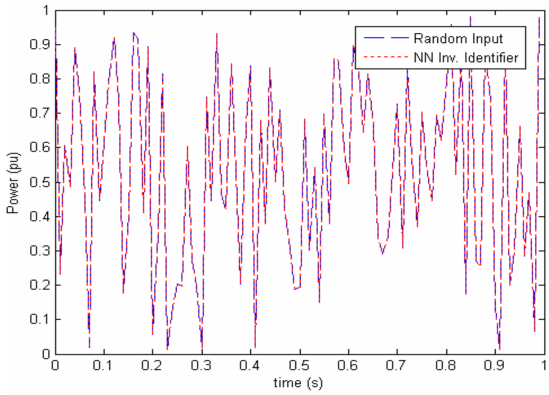

Figure 8: Time Response of Inverse Identification

5.2 Forward Identification

The second step involves developing neural network forward identifier. Training of the neural network identifier which is based on the linearized model of the wind turbine system takes place to generate suitable input/output training patterns to give enough information about the system. The number of neurons in the input layer has been chosen to be three neurons. The neural network identifier has been learned the forward dynamics of the system for 10000 epochs of training, where the training performance error reaches very low value of about $1.14546*10^{-17}$. More than 10000 epochs will not decrease the performance error with increase in the number of epochs. The next step in the design of neural control system is to check the existence of the plant model. This can be done by checking the sign of the system Jacobian at every sample in the regions of interest, which is not equal to zero at every sample.

5.3 Choosing Reference Model

One of the important design steps is choosing an appropriate reference model. A linear second order system is chosen as reference model which is described by:

$$G_{MR}(s) = \frac{P_{eMR}(s)}{P_{e\,\mathrm{Ref}}(s)} = \frac{25}{s^2 + 8s + 25} \qquad (22)$$

Introducing the model reference will stabilize the neural network controller and hence the output of the system converges with the desired output profile.

5.4 Control Algorithm and Results

An adaptive control algorithm is used for the purpose of the control system. The control algorithm performs the parameters required to control the wind turbine system. We have developed the back-propagation algorithm to have the capability of auto-switching technique, so that the controller switches its parameters according to the current operating point. For control purpose, three operating points are chosen to lie with the 11, 13, and 15 mps. The error of the adaptive back-propagation control algorithm is combined of neural model dynamics (forward identifier) and inverse dynamics of the system (inverse identifier). For the control purpose, the specified wind speed profile in section three is used. The actuation or regulation input is the pitch angle that is the output of the hydraulic actuator. The pitch angle is varied by the controller to track the desired output power of the generator. Applying the designed control system with the configurations and algorithms explained before, on-line time response simulation results are obtained for the output power of the generator, the mechanical torque, and pitch angle change in figures 9, 10.

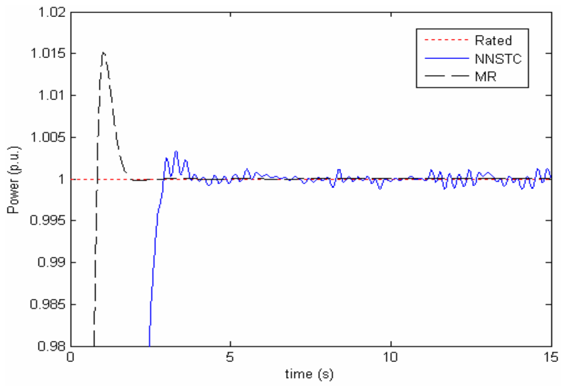

Figure 9: Time Response of the Controlled Output Power

The figure above represents good simulation results in the area of wind turbine systems. The controlled output power of the generator tracks the rated power as a result of the controlled torque response. The controlled output power has small value of oscillation of about 0.0015 p.u around the rated power, and maximum overshoot equal to 0.003 p.u. The settling time is equal to 3 seconds. Figure 10 shows time response of the pitch angle variation of the controlled system.

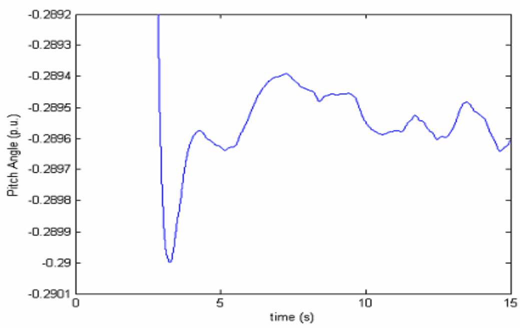

Figure 10: Time Response of the Pitch Angle of the Controlled System

The negative sign of the pitch angle change indicates that the effect of the pitch angle is opposite to the mechanical torque and hence the output power. The adaptive back-propagation with auto-switching technique affects the overall response of the system. During operation, the control algorithm switches the learning rate and momentum term according to the current operating point. The values of the learning rate and momentum term for the three operating points are tabulated in table 1.

Operating Point	Learning Rate (η)	Momentum (α)
11 mps	0.95	0.94
13 mps	0.9	0.85
15 mps	0.85	0.8

Table 1: Control Parameters versus Chosen Operating Points

The values of the learning rate and momentum term are chosen precisely to produce good performance. Increasing the learning rate makes the system faster.

6. CONCLUSIONS

The main objective of this work was the application of artificial neural networks as self-tuning control system to the wind turbine power generation systems. The simulation results of the controlled input mechanical torque, pitch angle and output power of the generator have proved that the proposed neural network is in fact an innovative contribution in the control field of horizontal axis wind turbine power generation systems. One of the essential factors of neural network control system design that affects the control system to produce the presented conclusion is the well trained neural networks inverse and forward identifiers.

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