Smart Pitch Control Strategy For Doubly Fed Wind Generation System Using Adaptive Neural Networks

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Abstract—This paper presents a study on smart pitch control strategy for a variable speed doubly-fed wind generation system. Non-linear as well as linearized dynamic models of the wind system pitch controller and the doubly fed induction generator including the drive train are developed. A PI controller is employed to generate the appropriate pitch angle for varying wind speed conditions using an adaptive artificial neural network (ANN) and a simple neural network (NN) to produce PI gain settings for various wind speed conditions. The training data, on the other hand, was generated through differential evolution (DE). Simulation studies show that the DE based adaptive ANN can generate the appropriate control to deliver the wind power to the generator efficiently with minimum transients.

I. INTRODUCTION

Early wind farms were dependent on induction generators and so they were fixed speed wind turbines. This considerably reduces their overall efficiency. These days emphasis are being laid on variable speed wind turbines (VSWT). Amongst the VSWT we have permanent magnet synchronous generators (PMSG) and doubly fed induction generators (DFIG). In wind generation systems, DFIG is preferred over PMSG. The variable speed operation is carried out by using voltage controlled inverters (AC-DC-AC), which convert power at varying frequencies at the variable-speed generator to DC, and then use some form of power electronics to convert the DC power back to AC at a fixed frequency appropriate for the grid connection.

The synchronous type of generator has the capability of direct connection (direct-drive) to wind turbines, with no gearbox [1], [2]. This advantage is favorable with respect to lifetime and maintenance. Synchronous machines can use either electrically excited or permanent magnet (PM) rotor. The PM and electrically-excited synchronous generators differ from the induction generator in that the magnetization is provided by a permanent magnet pole system or a dc supply on the rotor, featuring self-excitation property. Self-excitation allows operation at high power factors and high efficiencies for the PM synchronous generators.

On the other hand, the DFIG equipped wind turbines are fast becoming popular. When compared with conventional induction generators, the DFIG may have several advantages which depend on how the frequency converter control is arranged, as in [3]. They have the ability to control reactive power and support grid voltage and the decoupled control of active and reactive power, i.e. independent torque control and rotor excitation current. The overall efficiency of the modern day wind turbines increases using variable speed wind turbines (VSWT) [4]. Also, the DFIGs come in various sizes of up to 10 MW as compared to PMSGs, which can provide a maximum power of up to 2 MW. Hence, DFIGs are best suited for pitch-controlled variable speed wind turbines.

Wind turbines in general have two main controls. The mechanical control which includes the blade pitch control and the electrical control which covers the control of the power converters and the load side control. The control of blade pitch angle is a necessary part of variable speed wind turbines as by controlling the pitch angle, we can control the aerodynamic power that flows through to the generator [5]. By carefully controlling the pitch angle, we can allow for maximum power being delivered to the generator at a particular wind speed to which the turbine is exposed to [6].

The system dynamics using the PI controller have been described in [7], [8]. Fuzzy logic was used in [9] to find the pitch controller parameters. A self tuning fuzzy-PID controller was proposed in [10]. Robust controllers for output power leveling of variable speed variable pitch wind turbine generator systems are also available in literature. The use of generalized predictive control has been reported in [11], [12]. A neural network capable of self tuning for during different operating conditions has been reported in [13]. The proposed controller consists of neural networks inverse and forward identifiers for modeling the dynamics of the system.

One of the challenging aspects of wind generation system is to extract maximum power from randomly changing wind conditions. At the same time the turbine should have higher efficiency to transfer maximum power to the grid. In this work, a variable speed DFIG system is investigated for pitch control. Pitch controller parameters are found using an adaptive intelligent control for maximum power transfer from wind and the results are compared.

A complete dynamic model of DFIG equipped with pitch controller is developed. The adaptive pitch control strategy making use of the back propagation algorithm and differential evolution is then described.

II. SYSTEM MODELING

A schematic diagram of the DFIG system connected to the power grid equipped with pitch control is shown in Fig.1. The induction generator is driven by a horizontal axis wind turbine through its gear boxes. The converters are located between the rotor terminals and the grid. The dynamic model of the system
includes the wind turbine, pitch controller and the generator with its converters.

A. Wind turbine Dynamics

The amount of power extracted from wind is a function of air density and is given by [14],

$$ P_m = \frac{1}{2} \rho \pi R^2 V_w^3 C_p(\lambda, \beta) $$

Here, $V_w$ is the wind velocity, $R$ is the radius of the rotor blades and $C_p$ is the power coefficient that is dependent upon the tip speed ratio $\lambda$ and the pitch angle $\beta$. The power coefficient $C_p$ is a non-linear function of $\lambda$ and $\beta$ given as,

$$ C_p(\lambda, \beta) = 0.5176 \left[ \frac{116}{\lambda_i} - 0.4\beta - 5 \right] e^{\frac{-2\beta}{\lambda_i}} + 0.0068\lambda $$

$$ \frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} $$

B. Drive Train Modeling

The drive train modeling includes the high inertia turbine with a low inertia generator rotor through a relatively soft shaft given by (3)-(5), where, $\omega_t$, $\omega_r$ and $\omega_c$ are the turbine speed, rotor speed and base system speed in p.u respectively. $K_s$ is shaft stiffness, $\theta_s$ is the torsional twist angle, $H_t$ and $H_g$ are turbine and generator inertia respectively, $\Delta s$ is the change in slip and $P_e$ is the electrical power.

$$ \dot{\omega}_t = \frac{P_m - K_s\theta_s}{2H_t} $$

$$ \dot{\theta}_s = \omega_c (\omega_t - \omega_r) $$

$$ \Delta s = \frac{K_s\theta_s - P_e}{2H_g} $$

C. Pitch Angle Control

As can be observed from (1) and (2), control of pitch angle provides an effective means for controlling the power input to the generator under varying wind speeds. The blades are provided the necessary pitch angle through pitch servos. This may be hydraulic or electrical systems. Conventional pitch angle control use PI controllers to generate the appropriate $\beta$. The pitch servo system compares the measured angle of $\beta$ to the reference and corrects the error. Here $\hat{\beta}_i$ is an intermediate output from the controller. Usually a first order servo model is sufficient in investigations of power system stability. However, more detailed pitch servo models may also be used.

In order to get more realistic response of the generic, regular pitch control, a number of delay mechanisms must be implemented in control system models. Such delays represent sampling and filters, damping natural frequencies in wind turbine construction. Figure 3 shows a popular method of employing the pitch control which makes use of the generator power as a feedback signal compared with the reference mechanical power available from wind.

D. Non-Linear Model

Combining the dynamics of generator, drive train, converter circuits and the pitch controller, the composite dynamic model
Figure 4: The Back Propagation net layout

can be written as,
$$\dot{x} = f[x, u]$$

(6)

Here, $x$ is the vector of the states consisting of $[i_d, \theta_q, i_d, \omega_1, \theta, \omega_r, i_d, \omega_1, \omega_q, \beta_1]$ and $u$ is the pitch control. In this work the gains of the PI controller are obtained from a trained artificial neural network (ANN).

E. Linearized System Model

The linearized of (6) can be expressed as,
$$\dot{x} = Ax + Bu$$
$$y = C\dot{x} + Du$$
(7)

Where, the states are the perturbations of the original state variables in (6). Note the linearization process requires finding $\Delta P_m$, which can be written as,
$$\Delta P_m = K_1 \Delta \omega_1 + K_2 \Delta \beta$$
(8)

where $K_1 = \frac{\Delta P_m}{\omega_1}$ and $K_2 = \frac{\Delta P_m}{\Delta \beta}$.

The wind data for the training was collected from the 5-kW wind system installed at the King Fahd University beach front. The training data was generated by a differential evolution technique. A brief outline of the ANN and DE procedures are given in the following.

III. BACK PROPAGATION NEURAL NETWORK

Figure 4 shows the basic configuration of a back propagation based neural network with $L$ layers and with $x_p$ as the input layer and $T_p$ as the output layer. The intermediate layers, $N_i$, are the hidden layers of the network. The training of the neural network is supervised i.e. the network receives both the raw data as well as inputs and targets as outputs. The learning involves adjusting the weights of the network such that sum of square error given by (9) will be minimized.

$$E(W) = \frac{1}{2} \sum_{k=1}^{N_L} [z_{lk}(x) - T_k(x)]^2$$
(9)

where, $E$ is the sum of square error of all the weights $W$, $x$ is the input vector, $T_k$ is the set of target vector and $N_L$ is the number of neurons in layer 1 and $z_{L,k}$ represents the output of the neuron given by (10).

$$z_{lk} = \sum_{j=1}^{N_{L-1}} w_{ljk} z_{l-1,j} \cdot f$$
(10)

The output of the neuron is transferred to another layer using an activation function, which is a sigmoid function in this case given by (11).

$$f(t) = \frac{1}{1 + e^{-ct}}$$
(11)

The updating of weights for the neural network takes place at each time step and is represented by (28).

$$w_{lj}(t + 1) = w_{lj}(t) - \mu \frac{\partial E(W)}{\partial w_{lj}}|_{W(t)}$$
$$= w_{lj}(t) - \mu \sum_{p=1}^{P} \frac{\partial E(W)}{\partial w_{lj}}|_{W(t)}$$
(12)

where $\mu$ is a learning parameter used for tuning the speed and quality of the learning process. The neural network is said to be trained once the change in error, in weights is minimized given by $\frac{\partial E(W)}{\partial w_{lj}}$.

A. Differential Evolution

The DE is a evolutionary search algorithm which finds the optimum value of an objective function subject to satisfying the system constraints [15]–[17]. This makes use of crossover and mutation factors that allow to search for the global optima in the entire search environment between the upper and lower bounds of the control variables that need to be optimized; in this case the controller parameters $K_p$ and $K_i$. In order to choose between the new members that are produced during the mutation and crossover stages, there is a process of survival of the fittest based on the objective function. The objective function, $J$, chosen for this particular problem is to minimize an eigenvalue based function given by,

$$J = \sum_{l=1}^{n} (\zeta_l - \zeta_0)$$
(13)

where $n$ represents the eigenvalues of the linearized system of the original non-linear system, $\zeta$ is the damping ratio of a particular eigenvalue and $\zeta_0$ is the predefined damping which has to be achieved during optimization.

IV. ADAPTIVE NEURAL NETWORK

Figure 5 shows the adaptive pitch control strategy employed for DFIG. The strategy involves making use of input wind speed and setting the reference power by making use of Fig.2. The reference neural network model uses a back propagation based neural network which sets the PI gains as targets with random wind speeds as inputs. Using differential evolution, the training data for this neural network is obtained. The PI gains obtained from DE are optimal gains by making use of eigenvalue based objective function.

As the wind speed varies, the system dynamics change. This change in system states must be reflected by adapting the weights of the neural network accordingly. The reference neural network model as described earlier sets the desired controller gains as targets for the adaptive ANN while it tries to adapt the weights to achieve them. This adaptive ANN provides the optimum pitch settings to the wind turbine.

Since the back propagation based neural network takes wind speeds as the only input with targets set as controller
gains, an adaptive neural network is developed that caters for variation in system states including the changes in wind speeds. For this the weights of the neural network need to be updated at each time step in order to achieve the desired targets set by the reference neural network model. The adaptive neural network makes use of $\mu$-LMS (Least Mean Square) algorithm [18]. This algorithm works by performing approximate steepest descent on the weights. An instantaneous gradient, based upon the square of the instantaneous linear error is defined by (14).

$$\nabla E_t = \frac{\partial e_t^2}{\partial W(t)} = \left[ \frac{\partial e_t}{\partial w_{0t}} \right]$$

In (14), $\epsilon_t$ holds the instantaneous errors for the neural network, while $\nabla E_t$ is a matrix of gradients of errors with respect to the respective weights $w_0 \ldots w_N$ in the weight matrix $W$. The weight update is carried out by,

$$W(t+1) = W(t) - \mu \nabla E_t$$

$$W(t+1) = W(t) - \mu \frac{\partial e_t^2}{\partial W_t}$$

where, the weight matrix is updated at each time instant $t$, with a given learning parameter $\mu$. The instantaneous gradients are available from the training data. Computing these would involve averaging the instantaneous gradient associated with all patterns in the training set. Applying differentiation on (15) gives,

$$W(t+1) = W(t) - 2\mu \epsilon_t \frac{\partial e_t}{\partial W_t}$$

(16)

$\epsilon_t$ gives the linear difference between the desired response at any stage $d_t$ and the output $W_t^T x_t$. Replacing $\epsilon_t$ in (16) results in,

$$W(t+1) = W(t) - 2\mu \epsilon_t \frac{\partial (d_t - W_t^T x_t)}{\partial W_t}$$

(17)

Noting that $d_t$ and $x_t$ are independent of the current instant of weight value $W_t$, (17) becomes:

$$W(t+1) = W(t) + 2\mu \epsilon_t x_t$$

(18)

The learning constant $\mu$ determines the stability and the convergence rate as discussed in the previous section. In this algorithm, and other iterative steepest descent procedures, use of the instantaneous gradient is perfectly justified if the step size is small.

V. SIMULATION RESULTS

A wind gust is applied to the system’s initial conditions. These gusts are generally longer and often unpredictable. Figure 6 shows the wind speeds as taken from the KFUPM beach front and also taking a snapshot of the first 10 sec of these wind speeds for simulation purposes. In this section, system performance of a pitch controller designed with adaptive neural network is compared with that designed with a simple neural network trained with wind speeds only and a nominal control i.e. $K_p = 1$ and $K_i = 0$. Figures 7-14 show the dynamic performance of the doubly fed induction generator and the controller response to such a gust. A controlled response of the generator speed, terminal voltage stator current and rotor current with the adaptive neural network based pitch controller is observed from Figs. 8-11. The transients are reduced significantly as compared to the nominal control as these states change under the given wind conditions.

Figure 7 shows the variation in mechanical and electrical power. As the pitch angle adjusts to sudden changes in wind
speeds as illustrated in Fig. 14, the mechanical power also varies accordingly. From the electrical power plot, it is clear that the output power tracks the mechanical power that is available from the wind. It is also observed that contrary to the rapid changes in mechanical power, the electrical power supplied by the wind generator is smooth with minimum transients with an adaptive neural network based pitch controller. The pitch angle variation can be compared with the wind speed data. The primary purpose of the pitch controller is to reduce the pitch angle when the wind speed goes below the rated wind speed and vice versa. Comparing the results of Fig. 7 with Fig. 14, it is concluded that the pitch controller is performing the same task.

The controller parameters are updated regularly with changes in wind speeds and system states. This is clear from Figs. 12 and 13. This continuous update of gains allows for increased damping of the states. The nominal control is unable to cope with random change in wind speeds and hence results in minimum damping and poor system response as compared to the adaptive neural network based controller. The adaptive ANN based pitch controller also has superior performance over the pitch controller making use of simple neural network in terms of better damping of transients and mechanical power transfer to the generator. The controller parameters in the case of nominal control are set to their original values throughout the simulation time.
The paper presented a complete dynamical model of DFIG system equipped with converter circuitry and pitch control. The model consists of the generator, wind turbine aerodynamic and the converter systems. A smart pitch control strategy, which adaptively tunes the controller parameters. The strategy involved generation of the controller gains for the range of wind speeds through a differential evolution technique, training the control parameters through a back propagation neural network and adaptively tuning the network weights for random wind speeds and variable operating scenarios. The pitch controller parameters were optimized using the differential evolution intelligent technique, which made use of an eigenvalue based objective function to obtain the optimized values.

From the simulation results, it is observed that the pitch controlled system employed enables the electric power to track the mechanical power from wind by varying the pitch angle of the blades. The adaptive neural network based pitch controller generates the necessary control to keep the system stable with minimum transients. The adaptive ANN controller was compared with nominal control scenario and with a simple neural network, which were unable reduce the system transients and were also incapable to allow the output power to track the available wind power properly.

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