Fuzzy gain scheduled output feedback control for variable-speed variable-pitch wind turbine

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Abstract—This paper proposes a fuzzy gain scheduled output feedback control for variable-speed variable-pitch wind turbine in full load region. The proposed method is based on modeling the nonlinear system as a family of systems linearized around a specific operating point. The goal is to design optimal PI controllers based on linear models and a fuzzy scheduler. The parameters of each PI controller are optimized using PSO algorithm. At each sampling time, the scheduler assigns weights to each local PI controller. The weighted sum of local PI controller outputs is used as an input control for manipulating the pitch angle to maintain the speed generator around its rated value. The effectiveness of the proposed controller has been proven in the Matlab / Simulink environment.

Keywords: Wind turbine, Pitch control, PI controller, Fuzzy scheduler, Particle Swarm Optimization (PSO).

I. INTRODUCTION

In our days, the wind is the renewable energy technology the most widely used in power systems, because it is a safe type of energy, clean, endless and respectful of nature. For this, many countries are interested in investing in wind energy conversion systems (WECSs) precisely wind turbines.

For good operation of wind turbine at all wind speed regions, control techniques play a very important role to improve their performance and reliability. The variable speed operation allows the continuous adjustment of rotational speed of wind turbine (accelerated or decelerated), such fate as, the wind turbine operate in high aerodynamic efficiency. In the case of variable speed, wind turbines operate in two primary regimes, below-rated wind speed and above-rated wind speed.

In the first one (partial load region), the goal is to capture the maximum energy available in the wind, by adjusting the turbine rotational speed. In the last one of full power region, above rated wind speed, the primary objective is to maintain a constant power output. It is generally achieved by controlling the pitch angle and generator torque. Thus, in order to control the pitch angle in wind turbines, various methods have been used. Fuzzy Predictive Control of Variable Speed Wind Turbine presented in [1]. In [2] Supervisory control of a variable speed wind turbine with doubly fed induction is used. An RBF neural network based PI pitch controller for a class of 5-MW wind turbines using particle swarm optimization algorithm used in [3]. In [4] adaptive fuzzy sliding-mode control in variable speed proposed for adjustable pitch Wind Turbine. A method for pitch angle controller using Fuzzy logic systems for smoothing wind power fluctuations during below rated wind incidents presented in [5]. An optimal LQG controller for variable speed wind turbine based on genetic algorithms for controlling the pitch angle is presented in [6].

A study of stability performance analysis for variable-speed variable-pitch WECS based on dynamic Feedforward neural network control is presented in [7]. In [8], Pitch angle control of variable low rated speed wind turbine using Fuzzy Logic controller is used and in [9] Pitch control for large scale wind turbines based on feed forward fuzzy-PI is used.

Nowadays, one of the most challenges of engineers, is the control of variable speed variable pitch wind turbine above rated wind (full load regime). One of the main motivations for the design of controllers for wind energy conversion systems (WECS) in this region, the existence of an important fluctuation applied to the input turbine power, caused by the erratic variation in the wind speed. This fluctuation can cause the reduction in the life of the WECS components.

In this paper we are interested only by the operation in the full load regime. The design of wind turbine controller is not a simple task. It’s due to non linearity of system, variation of wind speed, the existence of variables strongly coupled and over its multi-variable structure (MIMO).

Proportional and integral (PI) controller is the most popular control scheme that has been widely implemented throughout the wind energy conversion systems. The basic PI controllers have difficulty in controlling processes, and precisely wind energy conversion systems with complex nonlinearity. Recently, many intelligent techniques have developed to make it working under these difficulties so that the closed loop system still gives satisfactory results. There are many methods to describe the nonlinear wind system in the form of several linear models [10], [11].

It is essential to note that the use of PSO algorithm for determining the optimal PI gains using PSO is not suitable for variable wind speeds because PSO for any selected constant wind speed above the rated value, provides a pair of gains (Kp and Ki), correspondingly. However, a pair of gains which is optimal for a specific wind speed is not optimal for another. Thus, we need an intelligent system which is based on the...
above optimal data set calculates the optimal PI gains for each wind speed variation. In [3], Iman et al, have used an RBF neural network based PI pitch controller for a class of 5-MW wind turbines using particle swarm optimization algorithm. The proposed method uses an RBF neural network to calculate the optimal gains of the PI controller, based on the variations in wind speed profile. PSO algorithm is used for some constant wind speeds above the rated value to drive the optimal PI gains. The PI controller tunes the pitch angle such that the difference between actual and nominal speed of the generator is minimized.

The control scheme proposed in this paper consists of a family of controllers PI (local controllers) and a scheduler [10]. At each sampling time, the scheduler, based on fuzzy logic, assigns weights to each controller. The weighted sum of the outputs, which is an interpolation of the local controller outputs, will be applied as an input to the plant. The main contributions of this paper are as follows: firstly, the nonlinear system is represented as a family of local linear state space models. Secondly, local PI controllers have been designed according to a Particle Swarm Optimization (PSO) and this for each local linear model. The weighted sum of the local PI controller outputs has been used to control the nonlinear process.

This paper is organized as follows: Section 2 describes the wind turbine model. Section 3 presents the different wind turbine operating range. Section 4 deals with the nonlinear PI controller design based on multiple PI controllers of local models. Section 5 explains briefly PSO algorithm. Before conclusion in section 7, section 6 gives out the simulation results performed by a simulation model based on Matlab/Simulink. The correctness and effectiveness of the proposed strategy are verified by the simulation.

II. WIND TURBINE MODEL

The wind turbine studied in this paper is a horizontal axis variable-speed/variable-pitch wind turbines. Figure 1, demonstrates the general structure of the wind turbine model. The major components of this wind turbine model are the aerodynamics system, the drive-train, the generator and the pitch actuator.

A. Aerodynamics model

The aerodynamic torque of the wind turbine $T_{wt}$ is given by the following expression:

$$T_{wt} = \frac{1}{2} \rho \pi R^3 \frac{C_p(\lambda, \beta)}{\lambda} V^2$$

Where $\rho$ is the air density, $R$ is the blade length, and $V$ is the wind speed. $C_p$ is the power coefficient, is define by

$$C_p(\lambda, \beta) = c_1(\frac{C_2}{\lambda} - c_3\beta - c_4)e^{-\frac{\lambda}{c_5}} + c_6\lambda$$

(2)

Where $\beta$ is the pitch angle and $\lambda$ the tip ratio of wind turbine, which expressing the ratio between the peripheral blade speed and the wind speed, and computed as

$$\lambda = \frac{\omega_p R}{V}$$

(3)

And

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

(4)

The coefficients $c_1, ..., c_6$ are given by 0.5176, 116, 0.4, 5, 21, 0.0068 respectively [12]. The following figure gives the variation of $C_p$ as a function of $\lambda$ and $\beta$.

![Variation of $C_p(\lambda, \beta)$](Fig. 2. Variation of $C_p(\lambda, \beta)$)

B. Drive Train Model

The drive train system is representing by the following equations where, the wind torque and the electromagnetic torque, are the inputs, whereas the rotational speed is the output.

$$\begin{align*}
\dot{\omega}_r &= \frac{1}{J_r} T_{wt} - \frac{1}{J_p} \eta T \\
\dot{\omega}_g &= \frac{1}{J_g} T - \frac{1}{J_g} T_g \\
T &= K_s(i \cdot \omega_r - \omega_g) + B_s(i \cdot \omega_r - \omega_g)
\end{align*}$$

(5)

Where, $T_{wt}$ is the aerodynamic torque. $T_r$ is the electromagnetic torque. $J_r$, $J_f$ are inertia rendered at high shaft speed and low shaft speed, respectively. $\eta$ the efficiency, $i$ is the gear box ratio, $K_s$ is the shaft stiffness and $B_s$ is the damping coefficient.

C. Generator model

The generator model used in the wind turbine studied in this paper, is a simple first order model and accordingly, the
generator torque $T_g$ can be described as

$$\dot{T}_g = \frac{1}{\tau_g} (T_{g_{ref}} - T_g)$$  \hspace{1cm} (6)

Where $\tau_g$ is time constant of the generator and $T_{g_{ref}}$ is the torque set point. The generator power $P_g$ is obtained from the following equation:

$$P_g = T_g \cdot \omega_g$$ \hspace{1cm} (7)

Where $\omega$ is the generator speed.

**D. Pitch actuator model**

Fig.3, shows the model of the blade angle. The first block corresponds to the pitch controller to determine the reference angle $\beta_{ref}$ through the difference between the measured and the desired value of rotor speed. The second consists of an actuator which rotates the blades to a certain pitch angle $\beta$ equal to the desired angle one. The pitch actuator, is a nonlinear servo that can be modeled in closed loop as a first order dynamic system with saturation in the amplitude and derivative of the output signal.

$$\dot{\beta} = -\frac{1}{\tau} \beta + \frac{1}{\tau} \beta_{ref}$$ \hspace{1cm} (8)

where $\tau$ is the time constant of the pitch system.

**III. Wind turbine operating regions**

According to Fig.4, variable speed wind turbine operation can be divided into four regions [3]. Where, $V_{cutin}$, $V_{rated}$ and $V_{cutout}$ represent its boundaries. In this paper the values of $V_{cutin}$, $V_{rated}$ and $V_{cutout}$ respectively are 8m/s, 12m/s and 16m/s. Region 1 describes the start-up when wind speed is below $V_{cutin}$. Region 2 between $V_{cutin}$ and $V_{rated}$, which is called the partial load region. The main objective of controller in this region (Torque control) is to capture the maximum amount of energy from the wind. This is achieved by keeping the pitch angle approximately constant and using generator torque controller to vary the rotor speed. With small variation of pitch angle around the optimal value, a controller can also reduce dynamic loads in the process. Region 3, that is called full load region, between $V_{rated}$ and $V_{cutout}$ wind speed. The main control (pitch control) purpose in this region is to keep the generator speed $\omega_g$ around the rated generator speed $\omega_g^{ref}$ ei by zeroing speed error. This is accomplished by keeping generator torque constant and controlling blade pitch angles. When wind speed is upper than $V_{cutout}$, ie region 4, the wind turbine must be stopped, in order to its protection against the stresses and fatigue damages. The focus of this paper is on full load region (region 3) to design our controller.

**IV. Design of multiple model PI controller**

The PI controller is the most popular controller that have been used in wind turbine systems for the control of its speed and its power. This is due to their simplicity and rather high robustness. The small number of parameters enables for designer to rapidly arrive at satisfactory, although in many cases at optimal, system behavior. As stated in section 2 wind turbine dynamics change in nonlinear fashion with variation of wind speed. In this paper, we design a multiple model control system for controlling the pitch angle to maintain the output power at its rated value. It consists of three conventional proportional integral controllers (Local Linear Controllers) and a scheduler (input of scheduler is the wind velocity). Each PI correspond an operating regime of the wind turbine. At each sampling time the scheduler will assign weights $h_i$ for each controllers and the weighted sum of the outputs will be applied as input to the plant. For each variation of wind speed, the scheduler will make its decision. Fig.5, shows the proposed controller for wind turbine, which regulate the output in accordance with the error $e$ between generator rotor speed $\omega_g$ and its upper limit value $\omega_g^{ref}$. 

![Fig. 4. Evolution of PSO algorithm](image-url)

![Fig. 5. The proposed controller](image-url)
To design the proposed controller, we must take the non-linear model of wind turbine represent by Eq.9 and linearize it around chosen operating point \((\omega_{op}, \beta_{op}, V_{op})\).

\[
J_g \frac{d\omega_r}{dt} = T_{mech} - T_g \tag{9}
\]

The following equation gives a mathematical description of the system which combines the rotor and the gearbox (low-speed and high speed shafts) of wind turbine where \(J_g\) is the moment of inertia, \(T_{mech}\) is the mechanical torque necessary to turn the generator and \(T_g\) is the aerodynamic torque represented by equation \((5)\). After the linearization of Eq.9 around a specified operating point and transition to Laplace domain, simple algebraic manipulations yield the transfer function \((\text{Eq.10})\) that is needed for controller design.

\[
G_p(s) = \frac{\Delta \omega_r(s)}{L_v \Delta V(s)} = \frac{1}{s - L_{\omega_0}} \tag{10}
\]

Whither, the parameters \(L_{\omega_0}, L_v\) and \(L_{\beta}\) represents the wind turbine dynamics at the linearized point. Which are defined as follows: The aerodynamic torque \(T_{\omega}\) is a non-linear function. This non-linearity is due to the characteristic of the coefficient of performance \(C_p(\lambda, \beta)\) which is dependent of the wind speed, rotor speed and the pitch angle. The linearization of this equation around the operating point \((\overline{\omega}_r, \overline{V}, \overline{\beta})\), can be approximated as follows:

\[
\Delta T_{\omega r} = L_{\omega_0} \cdot \Delta \omega_r + L_v \cdot \Delta V + L_{\beta} \cdot \Delta \beta \tag{11}
\]

where \(L_{\omega_0}, L_v\) and \(L_{\beta}\) are defined as follows:

\[
\begin{aligned}
L_{\omega_0} &= \left. \frac{\partial T_{\omega r}}{\partial \omega_r} \right|_{(\overline{\omega}_r, \overline{V}, \overline{\beta})} = \frac{1}{2} \rho \pi R^3 V \frac{\partial C_p}{\partial \lambda} \bigg|_{(\overline{\omega}_r, \overline{V}, \overline{\beta})} \\
L_v &= \left. \frac{\partial T_{\omega r}}{\partial V} \right|_{(\overline{\omega}_r, \overline{V}, \overline{\beta})} = \frac{1}{2} \rho \pi R^2 V \left[ 2C_p - \lambda \frac{\partial C_p}{\partial \lambda} \right] \bigg|_{(\overline{\omega}_r, \overline{V}, \overline{\beta})} \\
L_{\beta} &= \left. \frac{\partial T_{\omega r}}{\partial \beta} \right|_{(\overline{\omega}_r, \overline{V}, \overline{\beta})} = \frac{1}{2} \rho \pi R^2 V^2 \frac{\partial C_p}{\partial \beta} \bigg|_{(\overline{\omega}_r, \overline{V}, \overline{\beta})}
\end{aligned} \tag{12}
\]

The symbol \(\Delta\) is used to represent the deviation of the variable from its operating point value. \(\overline{\omega}_r, \overline{V}, \overline{\beta}\) are the values of rotational speed, wind speed and the pitch angle of the wind turbine at the operating point, respectively. \(T_{\omega r}\) is the aerodynamic torque.

\[\text{V. PSO EVOLUTIONARY ALGORITHM}\]

Particle swarm optimization (PSO) is an evolutionary algorithm modeled based on social behavior of the bird flocks [13]. In this algorithm, components called particles, move in the search space of a function that we aim to minimize it. This function is called objective function. For each particle, the objective function value is calculated. Using a combination of the present and best previous position of the particle, a direction for its moving is selected. Moreover, the positions of the particles are influenced by experience and knowledge of themselves and their neighbors. These steps are repeated several times until the desired answer is achieved.

The speed \(V\) and the position \(Z\) of the particles are updated by the following equations[3]:

\[
\begin{align*}
V_{id}^{t+1} &= wV_{id}^t + c_1 r_1 (p_{best}^t_{id} - Z_{id}^t) + c_2 r_2 (g_{best}^t - Z_{id}^t) \quad (13) \\
Z_{id}^{t+1} &= Z_{id}^t + V_{id}^{t+1}, \quad i = 1, 2, \ldots n \quad (14)
\end{align*}
\]

where \(w\) is inertia weight factor. \(c_1\) and \(c_2\) are constants called confidence coefficients. \(r_1\) and \(r_2\) are two random numbers in the interval \([0,1]\). \(p_{best}^t_{id}\) is the best previous position along the \(d\)th dimension of particle \(i\) in iteration \(t\) and \(g_{best}^t\) is the best previous position among all the particles along the \(d\)th dimension in iteration \(t\). Fig.6 demonstrates the motion of a particle at one step of the PSO evolutionary algorithms. Its parameters given in Table.III In this paper, we have used optimals local PI controllers, the difference between rated and actual speed of the generator is minimized. To achieve this goal, the proposed controller should provide suitable pitch angle reference \(\beta_{ref}\) (that is mentioned in Section 2) in its output. Thus \(\beta_{ref}\) is obtained from the following equation:

\[
\beta_{ref} = \sum_{i=1}^{N} h_i(v) \ast \beta_i \tag{15}
\]

where,

\[
h_i \in [0,1], \sum_{i=1}^{N} h_i(v) = 1 \tag{16}
\]

---

**Fig. 6.** Evolution of PSO algorithm
and,
\[ \beta_i = K_{pi} e_i(t) + K_{ii} \int_0^t e_i(\tau) d\tau \] (17)
\[ e_i(t) = \omega_{ref} - \omega_{gi}(t) \] (18)

Where, \( \omega_{gi}(t) \) is the output of the \( ith \) local model, \( K_{pi} \) and \( K_{ii} \) are the proportional and integral gains of each PI controller, they have been optimized using the PSO method by minimizing the performance criteria (Mean Square Error (MSE)) for each variation of wind speed given by the following equation:

\[ J = \frac{1}{N} \sum_{1}^{3} h_i * (e_i)^2 \] (19)

According to Fig.6, after determining the initial values like swarm size and initial velocity of particles, PSO calculates the gains of PI controller for each particle and stores the MSE. Then according to the MSEs the best position of each particle is calculated and the best particle among the all particles in population is selected. This process is iterated while the number of iterations is equal with max iteration number and the best particle is selected after final iteration. In fact, the best particle contains the optimal PI gains which are corresponding to the MSE. Table.I shows the parameters of each PI controller at the operating points.

<table>
<thead>
<tr>
<th>wind speed</th>
<th>8m/s</th>
<th>12m/s</th>
<th>16m/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kp</td>
<td>12.1967</td>
<td>0.1956</td>
<td>4.5724</td>
</tr>
<tr>
<td>Ti</td>
<td>4.1549</td>
<td>3.3672</td>
<td>6.0978</td>
</tr>
</tbody>
</table>

**TABLE I**
PARAMETRES VALUES OF PI CONTROLLERS

VI. SIMULATION RESULTS

The numerical simulations have been performed on a 2 – MW wind turbine described in section 2. Whose characteristic are given in Table.II. The design of fuzzy scheduler feedback controller based on linear models developed at different operating regions, and the method to combine each PI controller output to yield a global controller output has been outlined.
in the previous sections. In this work we have intended to interpolate three PI controllers. In order to design the scheduler, wind speed profile shown in Fig.7 with 12 m/s average wind speed is used. Fig.8 result from fuzzy logic, shows the three operating region of wind turbine, each region corresponds to a wind speed (low, medium and high). The parameters of each PI controller are optimized using PSO algorithm, like shown in Fig.6 are given in Table.III. The pitch angle variation is given in Fig.9. We can see that, if the pitch angle of blades change, pitch actuator system uses less energy. Fig.10, we can observe that the proposed controller is able to keep generator speed around rated value (157 rad/s) with fewer variation. Fig.11 shows the error of speed generator of the proposed controller and the conventional PI controller, we can see that the error of proposed controller is in order of 10e-3 however the error of conventional PI controller is in order of 10e-2. Fig.12 shows that the proposed controller is able to keep the output power of generator around its rated value (2 – MW) but the fluctuations of generator power around the rated value in proposed controller is considerably acceptable. In According to the simulation results, it can be said that the proposed controller has an effective performance in pitch angle control.

VII. CONCLUSION

In this paper, a fuzzy gain scheduler controller based on local linear models for wind energy conversion system is proposed. A pitch controller has been developed to regulate the speed generator at rated value. From the simulation results it can be concluded that the proposed controller has good set-point tracking. The simulation results have shown the effectiveness of the proposed control system for wind turbine operating for each wind speed variation.

For further works we aim to decrease the fluctuations of the output and also improve the performance of the proposed method by considering other kinds of controllers as linear model predictive controller.

REFERENCES