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Research on A Novel MPPT Control Method for Variable-Speed Wind Power Systems

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Abstract: In this study, we build up the double-dynamic models of variable speed wind power systems and design a new type Maximum Power Point Tracking (MPPT) PI-NN controller to improve the precision of the Tip Speed Ratio (TSR) tracking based on the models. Moreover, the effect of the PI-NN controller and the PI-LQG controller are compared based on Matlab/simulation and the results show that precision of optimal TSR tracking using PI-NN controller is higher than that using the PI-LQG controller, output value of the TSR is optimized, thus more wind energy is captured.

Keywords: Maximum power point tracking, neural network, tip speed ratio, wind power systems

INTRODUCTION

The energy provided by wind has been gradually increased. Since the 1990 s last century, the global wind power industry has developed rapidly (Kittipong *et al*., 2007), wind energy has been gradually applied to many fields, for example, irrigation, navigation, grinding, city power supply. There are many MPPT control methods for maximizing the power (Camblong *et al*., 2006; Chun-Yao *et al*., 2009). However, these methods still exist shortcomings.

Neural Network (NN) control technology is widely used because of its advantages in dealing with nonlinear and uncertain and it has been gradually applied in the field of wind power systems (Giuseppe and Pietro, 2010; Bayat *et al*., 2010), literature (Yurdusev *et al*., 2006) using neural network to improve wind energy utilization coefficient and optimize Tip Speed Ratio (TSR) and achieve the ideal effect.

When wind speed is below rated value, simulation model of variable speed wind power systems is built up based on wind speed dual-dynamic models. MPPT PI-NN controller of optimal TSR is designed for variable speed wind power systems based on 6 kw wind generator, simulation results are compared with PI-LQG control of TSR based on literature (Inlian *et al*., 2008) and results show that precision of optimal TSR tracking using PI-NN control is higher than that using PI-LQG control, the TSR vulue is optimized, thus the largest wind energy is captured.

In this study, we study the maximum energy capture of variable speed wind power systems and build up dual dynamic model of variable speed wind power systems. Moreover, PI-NN controller is designed to improve tracking precision of the opitmal RST value. Comparing the PI-LQG control method in literature (Inlian *et al*., 2008) with the PI-NN. The results show that the optimal RST value can be obtained by the PI-NN controller and thus the maximum wind energy can be captured.

MODELLING OF VARIABLE SPEED WIND POWER SYSTEMS

Modelling of wind wheel: The variable speed wind power systems are mainly composed of wind wheel, transmission system, asynchronous double-fed generator. Mechanical power-P_{wt} and wind wheel torque Γ_{wt} can be expressed as:

$$P_{wt} = 0.5\pi\rho R^2 C_p(\lambda) v^3 \quad (1)$$

$$\Gamma_{wt} = \frac{P_{wt}}{\Omega_l} = 0.5\pi\rho R^3 v^2 C_\Gamma(\lambda)/\lambda \quad (2)$$

where, ρ is air density, R is radius of the wind wheel, v is wind speed, λ is TSR and $\lambda = \Omega_l R/v$, Ω_l, is wind wheel speed, $C_\Gamma(\lambda)$ is torque coefficient, $C_P(\lambda)$ is utilization coefficient of wind energy.

Modelling of wind speed: As two spectral ranges identified in the wind dynamics, wind speed can be expressed as:

$$v = v_{s+\Delta v} \quad (3)$$

where, v_S is slow dynamics wind speed, Δv is fast dynamic wind speed, Δv can be expressed as:

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$$\Delta v = -\frac{1}{T_w}\Delta v + \frac{1}{T_w}\xi \tag{4}$$

where, ξ is a white noise, T_w is filter time constant and $T_w = L_t/v_s$, L_t is pulse length of wind speed.

Modelling of wind power systems: Mechanical characteristics of wind wheel can be obtained by literature (Inlian *et al*., 2008):

$$\Gamma_{wt} = \Gamma_{ws} + \Delta\Gamma_{wt} \tag{5}$$

$$\Omega_l = \Omega_{ls} + \Delta\Omega_l \tag{6}$$

where, Γ_{ws} is slow dynamics wind wheel torque, $\Delta\Gamma_{wt}$ is fast dynamics wind wheel torque, Ω_{ls} is slow dynamics generator speed, $\Delta\Omega_l$ is fast dynamics generator speed. First-order model of wind power systems can be expressed as:

$$P_a = \Gamma_h\left[J_1\Gamma_{wt} - J_2\Gamma_h + \Gamma_h\Omega_l / \Gamma_h\right] \tag{7}$$

where,

$$J_1 = 1/J_w \tag{8}$$

$$J_2 = -\, i/J_w\eta \tag{9}$$

P_a is generator output power, J_w is torque inertia of the wind wheel, i is the ratio of gear box, η is transmission efficiency. Γ_h is wind generator torque. Dual dynamic models of wind power systems is given by Eq. (10)-(11):

$$P_{as} = \Gamma_{hs}\left[J_1\Gamma_{wt} - J_2\Gamma_{hs}\right] \tag{10}$$

$$\Delta p_a = \eta / J_l\left(\Delta k_1 + k_{1s}\right)\Delta p_a + \eta / J_l\Gamma_s\left[\left(\Delta k_2 + k_{2k}\right)\Delta v\right] \tag{11}$$

where, ΔP_a is fast dynamics generator power, p_{as} is slow dynamics generator power, k1 and k2 are given by Eq. (12)-(13). Γ_{hs} is slow dynamics generator torque, Ω_{ls} is slow dynamics wind wheel speed, Γ_{ws} is slow dynamics wind wheel torque:

$$k_1 = \frac{\Gamma_{ws}}{\Omega_{lS}}\frac{\partial C_T}{\partial\lambda} / \frac{C_T}{\lambda} \tag{12}$$

$$k_2 = \frac{\Gamma_{wS}}{v_S}\left(2 - \frac{\partial C_T}{\partial\lambda} / \frac{C_T}{\lambda}\right) \tag{13}$$

DESIGN OF PI-NN CONTROLLER

Design of PI controller: The wind energy utilization coefficient is maximized for a optimal tip-speed ratio value λ_{opt} when the blades pitch angle is $\beta = 0$. As is shown in Fig. 1, W_{hsr} is obtained by equation $W_{hsr} = il_r v_s/R$, the error between W_{hsr} reference value of slow dynamics generator speed and W_{hs} slow dynamics generator speed is token as input of PI controller, where $e = \Omega_{hsr} - \Omega_{hs}$, then output of the PI controller is G_{hsr}, which is reference value of slow dynamics generator torque.

Control structure of the compensator: It can be know: maximum value of wind energy utilization coefficient can be obtained by tracking optimal value of TSR. Structure of the neural networks compensator is 2-6-1, Levenberg-Marquardt (L-M) is token as the training function. Control structure of the neural network compensator is shown in Fig. 2, input of the compensator are the slow dynamics generator torque reference value Γ_{hsr} and output value of fast dynamics filter $\Delta\Gamma$.

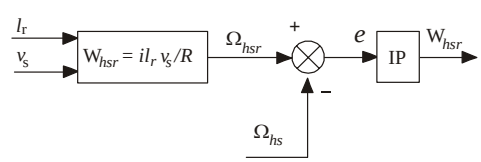


Fig. 1: Slow dynamics PI controller's structure of wind power systems

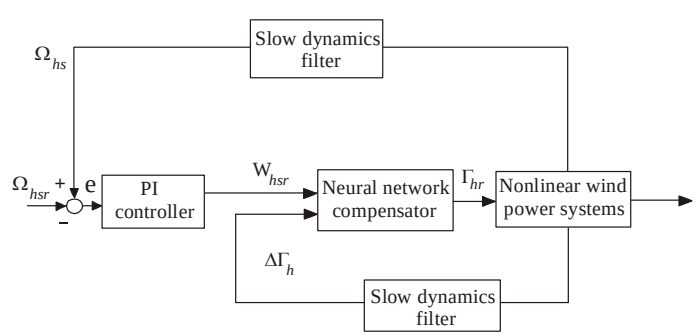


Fig. 2: Control structure of neural network compensation

Design of neural network compensator: Input of neural network in the input layer is as follow:

$$X = \left[x_1^{k-1}, x_2^{k-1} \cdots x_n^{k-1}\right] \tag{14}$$

where, x^k_{ij} is input from the j neuron in the k-1 layer to the i neuron in the k layer, inputs of neural network compensator for wind power systems are expressed as:

$$X_1 = \{\Gamma_{hsr1}, \Gamma_{hsr2}, \ldots \Gamma_{hsrm}\} \tag{15}$$

$$X_2 = \{\Gamma_{h1}, \Gamma_{h2} \ldots \Gamma_{hn}\} \tag{16}$$

sigmoid function of the neural network is expressed as:

$$x^k_i = f(net^k_i) \tag{17}$$

log sig function is selected as sigmoid function, weighting matrix is as follow:

$$W^k_{IJ} = \begin{bmatrix} w^k_{11} & w^k_{21} & \ldots & w^k_{ij} \\ w^k_{12} & w^k_{22} & \ldots & w^k_{ij} \\ \vdots & \vdots & \ldots & \vdots \\ w^k_{1J} & w^k_{2J} & \ldots & w^k_{IJ} \end{bmatrix} \tag{18}$$

$$net^k_i = X.W^k_{IJ} + \theta^k_j \tag{19}$$

where, net^k_i is the sum of input from the i-th neuron in the k-th layer, I is the number of neurons in the k-th layer, J is the number of neurons in the k-1-th layer. w^k_{ij} is weights from the j-th neuron in the k-1-th layer to the i-th neuron in the k-th layer. θ^k_j is threshold value from the k-1-th layer to the k-th layer. Neural network performance evaluation is expressed as Eq. (20):

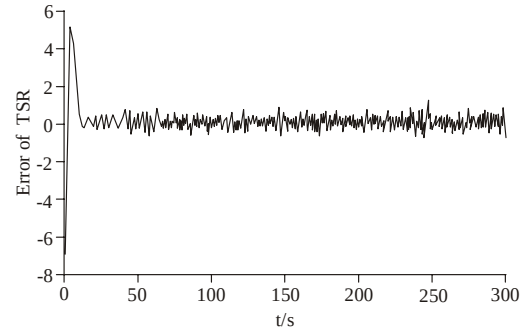
$$J = \min E\left(\int_{t=0}^{\infty} \left(O_{ti} - O_i\right)^2 dt\right) \tag{20}$$

Output target value of neural network is O_{ti} , where,

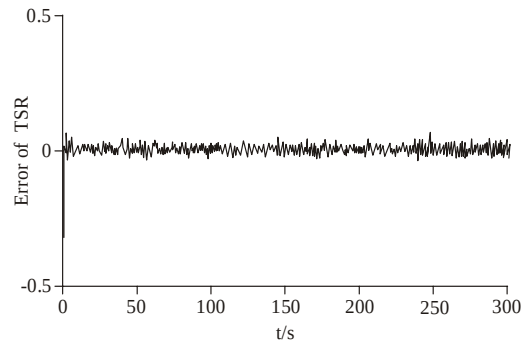
$$O^1_{ti} = \left\{\Gamma_{hr1}, \Gamma_{hr2} \ldots \Gamma_{hrn}\right\} \tag{21}$$

Γ_{hr} is reference value of the wind generator torque.

Simulation analysis: Electromagnetic subsystem is token as first-order inertia link, simulation models of wind power systems are built up based on Matlab/Simulink. Gearbox gear ratio i is 6.25, transmission efficiency of wind turbine η is 0.95, filter time constant\T_w is 10 s, air density is 1.25 kg/m^3, pulse length of wind speed L_t is 150 m, rated wind speed v_r is 12 m/s. According to Eq. (3)-(4), Wind speeds vary within a range of 4 and 10 m/s, mean wind speeds is 7 m/s. Reference value of the slow dynamics wind generator speed is token as reference input of the system, Ω_{hsr} is reference input of the system, where, Ω_{hsr} = 200 ad/S, 10 groups of neural network training samples can be obtained. The sample data is trained by off-line training mode. The output is shown in Fig. 3a to b after the system is stable.



(a) Error output of RST value with PI-LQG control



(b) Error output of RST value with PI-NN

Fig. 3: Output results

It can be seen by comparing Fig. 3a to b, change of the TSR range using PI-LQG control is larger; dynamic response properties of TSR with PI-NN neural network control is better, when wind speed is below, it can adjust TSR value to be fast-stable and close to the optimal value.

CONCLUSION

This research studies maximum energy capture of variable speed wind power systems. dual dynamic model of variable speed wind power systems is built up, PI-NN controller is designed to improve tracking precision of the opitmal RST value. Comparing the PI-LQG control method in literature (Inlian *et al*., 2008) with the PI-NN, results show that the optimal RST value can be obtained by the PI-NN controller and thus the maximum wind energy can be captured.

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