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Compensation Control Studies for Variable-Speed Wind Power Systems Based on Neural Network

***Abstract**. Wind power systems have strong nonlinear characteristic, when wind speed is below the rated value. A novel intelligent hybrid maximum power point tracking (MPPT) controller for variable-speed wind power systems is designed, linear parameter-varying (LPV) gain-scheduling controller is designed to regulate output of fast-dynamics generator torque, neural network compensator is used to eliminate the interference caused by unknown parameters, WPSO algorithm is used to train neural network. Hardware-in-loop simulation model is built up based on Matlab/Xilinx, results prove that the method can effectively improve wind energy utilization efficiency, mechanical vibration of wind turbine is reduced, the maximum wind energy is captured, a better idea is provide for application of FPGA in wind power field .*

***Streszczenie.** Zaproponowano nowy system sterowania systeme elektrowni wiatrowych uwzględniający zmienność szybkości wiatru. System wykorzystuje sztuczne sieci neuronowe co szybkiego sterowania dynamiką momentu. (**Kompensacyjny system sterowania elektrowniami wiatorowyumio o zmiennej szybkości wiatru – wykorzystujący sztuczne sieci neuronowe**)*

Keywords: wind power systems;tip speed ratio; wind energy utilization efficiency; maximum power point tracking.
Słowa kluczowe: system elektrowni wiatrowych, sterowania elektrowniami, śledzenie mocy.

Introduction

As an important part of the overall renewable energy sources, utilization of wind energy has become a global hot spot however, many control problems of wind power systems have not been solved. When wind speed is below rated value, common control strategy is maximum power point tracking (MPPT)[1], it is to capture the maximum power by controlling generator speed, the common control methods include PI control, linear parameter-varying(LPV) gain-scheduling control[2] etc, however, wind power systems have strong non-linear property caused by parameter variation, adaptive capacity of PI control is weak, real-time control is hard to be achieved; LPV gain control only guarantees the stability of the system, but interference of uncertain parameters is ignored, so the it is is not the ideal method.

Due to the approximation capacity of neural networks for nonlinear systems, neural network has been used in a wide range of applications, literature[3] uses neural network compensation control to suppress interference, stability of the wind power system is increased. Literatures [4]-[6] using neural network to improve wind energy utilization coefficient and optimize tip speed ratio.

Considering wind speed is below rated value,a novel intelligent hybrid MPPT controller is designed to capure maximum wind energy,weights of neural network are trained,in order to verify the validity of the method, the MPSO algorithm and PSO algorithm are compared. Hardware-in-loop simulation model of wind power systems are built up based on Matlab/Xilinx,results show the method can eliminate the interference caused by unknown parameters,the wind energy utilization coefficient is improved, mechanical vibration of wind power systems is reduced.

Normalized model for wind power systems

In order to get linear model of a variable speed wind power systems, linearized model of nonlinear wind power system is gotten around a steady-state operating point[7]. Letting $\bar{x}=x|_s$,then the error is $\Delta x = x-\bar{x}$, normalized error can be expressed as $\overline{\Delta x} = \Delta x/\bar{x}$.

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

(1) $$v = v_s + \Delta v$$

Where v_s is slow dynamics wind speed, Δv is fast dynamic wind speed, Δv can be expressed as:

(2) $$\dot{\Delta v} = -\frac{1}{T_w}\Delta v + \frac{1}{T_w}\xi$$

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. Normalized LPV model of the wind power systems can be obtained by literature [2]:

(3) $$\begin{cases} \dot{\boldsymbol{x}} = \boldsymbol{A}(\Theta)\boldsymbol{x} + \boldsymbol{B}(\Theta)\boldsymbol{u} + \boldsymbol{L}(\Theta)\boldsymbol{e} \\ \boldsymbol{z} = \boldsymbol{C}(\Theta)\boldsymbol{x} \end{cases}$$

Coefficient matrix of the LPV model depends affinely on the parameter vector Θ :

(4) $$\boldsymbol{A}(\Theta)=\boldsymbol{A}_0+\Theta\boldsymbol{A}_1$$

(5) $$\boldsymbol{B}(\Theta)=\boldsymbol{B}_0+\Theta\boldsymbol{B}_1$$

(6) $$\boldsymbol{L}(\Theta)=\boldsymbol{L}_0+\Theta\boldsymbol{L}_1$$

(7) $$\boldsymbol{C}(\Theta)=\boldsymbol{C}_0+\Theta\boldsymbol{C}_1$$

State vector $\boldsymbol{x}=\left[\overline{\Delta\Omega_l}\ \ \overline{\Delta\Gamma_{wt}}\right]^T$, control input vector $u=\overline{\Delta\Gamma_G}$, $\boldsymbol{L}(\Theta)=\left[0\ (2-\gamma)/T_w\right]^T$, $\boldsymbol{B}(\Theta)=\begin{bmatrix}-1/J_T \\ -\gamma/J_T\end{bmatrix}$, $\boldsymbol{A}(\Theta)=\begin{bmatrix}0 & 1/J_T \\ \gamma/T_w & \gamma/J_T-1/T_w\end{bmatrix}$. $\boldsymbol{C}(\Theta)=\begin{bmatrix}\frac{2}{2-\gamma} & -\frac{1}{2-\gamma}\end{bmatrix}$, $z=\overline{\Delta\lambda}$, $\overline{\Delta\lambda}$ is normalized error of tip speed ratio, $\overline{\Delta\Omega_l}$ is normalized error of wind wheel speed, $\overline{\Delta\Gamma_{wt}}$ is normalized error of wind wheel torque, $\overline{\Delta\Gamma_G}$ is normalized error of wind generator torque, $\gamma=\bar{\lambda}C_p'(\bar{\lambda})/C_p(\bar{\lambda})-1$, $C_p'(\bar{\lambda})=\left.\frac{dC_p(\lambda)}{d\lambda}\right|_{\lambda=\bar{\lambda}}$, $J_T=J_l\overline{\Omega_l}/\overline{\Gamma_{wt}}=J_h\overline{\Omega_h}/\overline{\Gamma_{wt}}$. Full-state feedback controllers is expressed as:

$$\boldsymbol{u}=\boldsymbol{K}(\Theta)\boldsymbol{x}$$

$\boldsymbol{K}(\Theta)$ is control gain matrix,the closed-loop system can be obtained:

(8) $$\begin{aligned} \dot{\boldsymbol{x}} &= \bar{\boldsymbol{A}}(\Theta)\boldsymbol{x}+\boldsymbol{L}(\Theta)e \\ \boldsymbol{z} &= \boldsymbol{C}(\Theta)\boldsymbol{x} \end{aligned}$$

where, $\bar{\boldsymbol{A}}(\Theta)=\boldsymbol{A}(\Theta)+\boldsymbol{B}(\Theta)\boldsymbol{K}(\Theta)$.

Compensator of wind power systems

Control structure of wind power systems

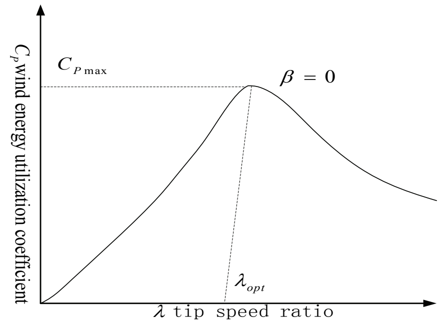


Fig.1 Tip ratio speed VS. power coefficient

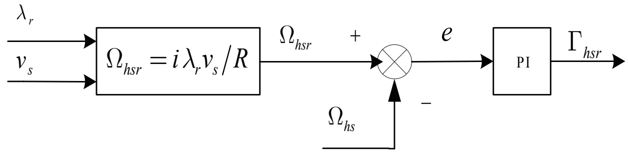


Fig.2 Slow-dynamic PI controller's structure of wind power systems

As is shown in fig.1, the wind energy utilization coefficient is maximized for a optimal TSR value λopt when the blades pitch angle is β = 0.As is shown in fig.2, Ω_{hsr} is obtained by equation $\Omega_{hsr} = i\lambda_r v_s / R$,the error between Ω_{hsr} reference value of slow dynamics generator speed and Ω_{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 Γ_{hsr} ,which is reference value of slow dynamics generator torque.

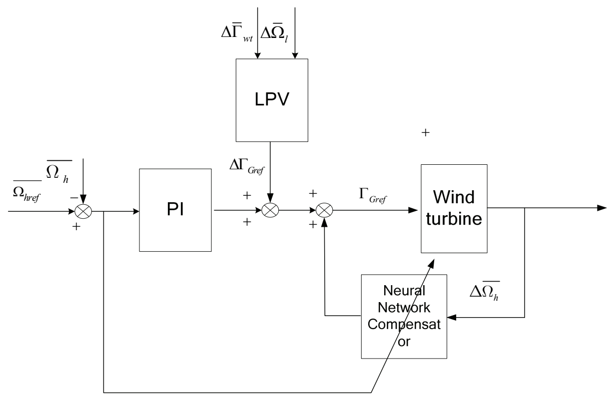


Fig.3 Control structure of wind power systems based on neural network compensation

PSO algorithm

Particle Swarm Optimization(PSO) was developed in 1995 by James Kennedy and Russell Eberhart.It can be expressed as:

$$v^{t+1}_{ij} = v^k_{ij} + c_1 \times rand_1() \times (pbest_{ij} - x^k_{ij}) + c_2 \times rand_2() \times (gbest_j - x^k_{ij}) \quad (9)$$

$$p^{k+1}_{ij} = p^k_{ij} + v^{k+1}_{ij} \quad (10)$$

Where, i is number of the particles, i=1,2,…,p; j=1,2,…,d; c_1 and c_2 are learning rates,and $c_1 = c_2 = 2$; $pbest_{ij}$ is best local position of each particle; $gbest_j$ is best global position; $rand_1(), rand_2() \in (0,1)$; $p_i = (p_{i1}, p_{i2}, \cdots, p_{id})$ is current position vector; $v_i = (v_{i1}, v_{i2}, \cdots, v_{id})$ is current velocity vector; $p^{k+1}{}_i$ is modified position vector; $v^{t+1}{}_i$ is modified velocity vector.

WPSO algorithm can be expressed as:

$$v^{t+1}_{ij} = w \times v^k_{ij} + c_1 \times rand_1() \times (pbest_{ij} - x^k_{ij}) + c_2 \times rand_2() \times (gbest_j - x^k_{ij}) \quad (11)$$

$$w = w_{\max} - L \times (w_{\max} - w_{\min}) / L_{\max} \quad (12)$$

Where, w is inertia weight factor,and $w_{\max} = 0.9$, $w_{\min} = 0.4$, L is number of the WPSO iterations, $L_{\max}$ is maximum number of the WPSO iterations.

Neural network compensator

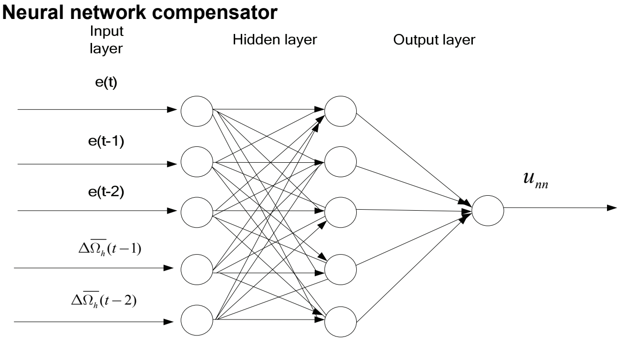


Fig.4 Structure of neural network compensator

As is shown in Fig.4,structure of neural network compensator is 5-5-1,there are 5 neurons in input layer, 5 neurons in hidden layer,and 1 neuron in output layer. $e(t)$, $e(t-1)$, $e(t-2)$, $\Delta\overline{\Omega}_h(t-1)$, $\Delta\overline{\Omega}_h(t-2)$ are input of the neural network compensator, u_{nn} is the output.

Simulation results

As is shown in Fig.5, hardware-in-loop simulation platform of wind power systems is built up based on Matlab/Xilinx, simulation parameters are given in table 1. Parameters of PI controller are: $K_p = -1$, $K_I = -25$. Parameters of LMI feasibility problems are solved by feast of LMI Toolbox,the control gain matrix is obtained:

$$\boldsymbol{K}(\Theta) = [-0.25576 \quad 0.01233] + J[-0.003145 \quad -0.0029]$$

Where J is a given positive number[9].Sigmoid function of neural network is logsig,training error is 0.01,Maximum number of the iterations is 200.

System Generator (SG) is the development of Xilinx's products ,it is based on Matlab /Simulink for the FPGA design,and it can be to simulate hardware and automatically achieve the required VHDL code also. Hardware implementation of neural network compensator can be implemented by literature[10].

Output of the wind energy utilization coefficient with PSO algorithm is shown in Fig.6 (i), output of the wind energy utilization coefficient with WPSO algorithm is shown in Fig.6 (ii),it can be seen the wind energy utilization coefficient in Fig.6 (ii) is stabler,and it reaches 0.47.Comparing Fig.6(iii) with Fig.6-(iv), error of generator torque with WPSO algorithm is samller than that with PSO algorithm.

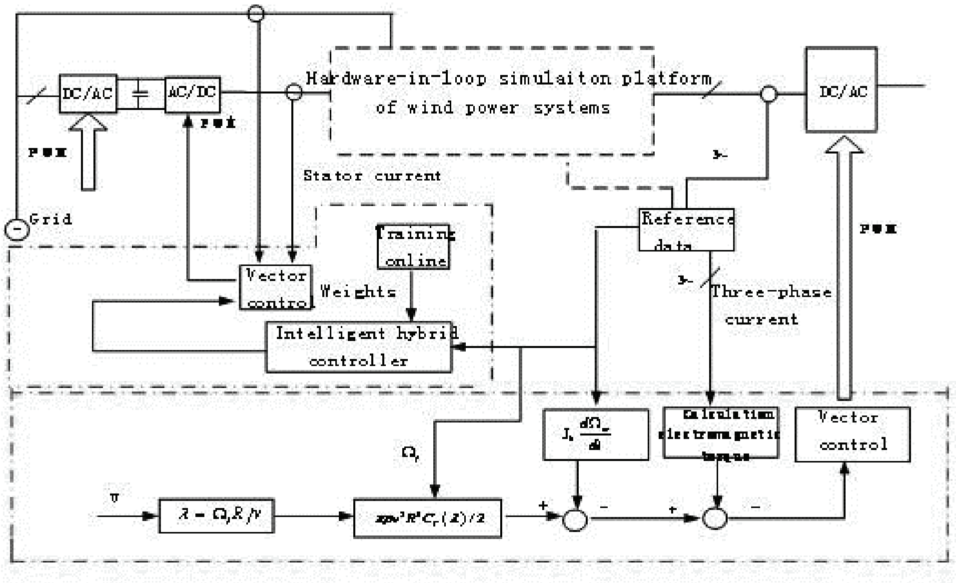
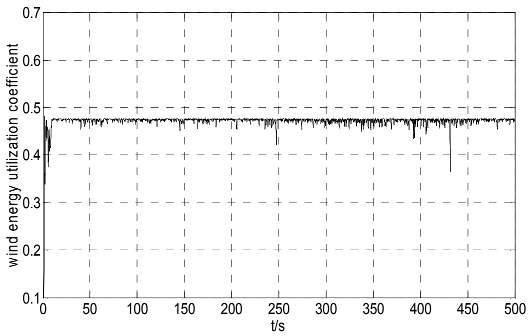
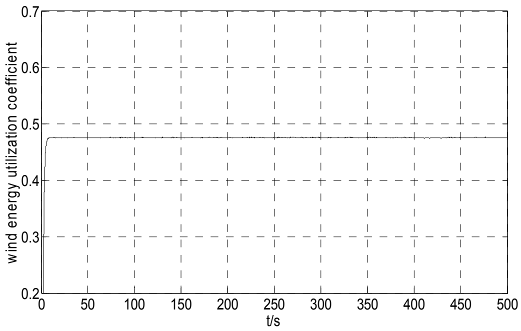


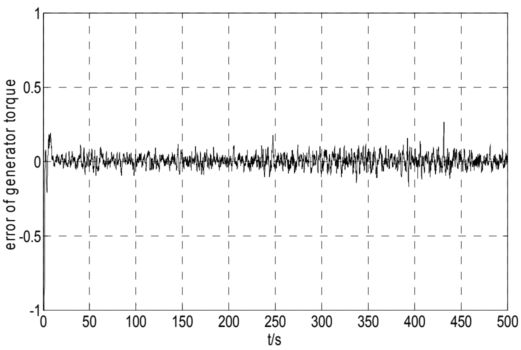
Fig.5 Hardware-in-loop simulation platform of wind power systems



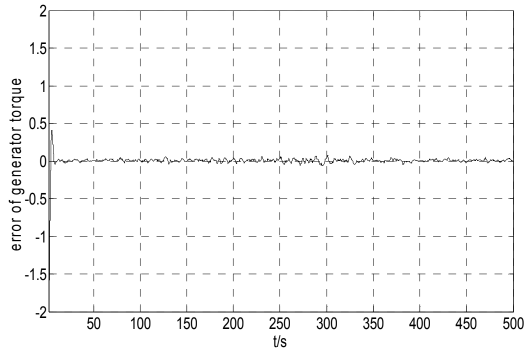
(i)Output of the wind energy utilization coefficient with PSO algorithm



(ii) Output of the wind energy utilization coefficient with WPSO algorithm



(iii) Error of generator torque with PSO algorithm



(iv) Error of generator torque with WPSO algorithm

Fig.6 Output results

Table 1 Corresponding parameter

Parameter Name	Parameter Name
Gearbox gear ratio\i	6.25
Transmission efficiency of wind turbine\ η	0.95
Filter time constant\ T_w	10s
Air density\ ρ	1.25kg/m^3
Pulse length of wind speed\ L_t	150m
Rated wind speed\ v_r	12m/s
Maximum value of wind energy utilization coefficient \ C_{pmax}	0.47

Conclusion

A novel MPPT intelligent hydrit controller is designed in this paper,neural network compensator is used to eliminate the interference caused by unknown parameters,the PSO algorithm and the WPSO algorithm are compared based on the neural network compensator with the same structure. Hardware-in-loop simulation platform of wind power systems is built up,results show that the method can capture maximum wind energy and reduce disturbances of wind power systems caused by unknown parameters.

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