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Stability Performance Analysis for Variable-Speed Variable-Pitch WECS Based on Dynamic Feedforward Neural Network Control

***Abstract**. Wind energy conversion system (WECS) is a complex nonlinear system, when the wind speed is above the rated value. For a smooth integration of wind generators into the utility grids, two subsystems are built for the WESC based on two-time-scale. NNPID compensator is designed to compensate slow dynamics blade pitch angle, in order to reduce fluctuations of the power output. Compensator for the slow dynamics blade pitch angle is designed based on dynamic feedforward neural network (DFNN), its approximation capabilities are verified by the SCADA (supervisory control and data acquisition) wind farm data collected. Control performances of the DFNN with different structure are compared and analysed, results show that the method can effectively reduce the interference caused by disturbed parameters of the WECS. Safety of the system is improved, and a better idea is provided for application of the DFNN in wind power systems field.*

***Streszczenie.** System konwersji energii wiatrowej jest szczególnie złożony gdy prędkość wiatru przekracza założone wartości. Zaproponowano dynamiczny układ sterowania z siecią neuronową DFNN. Osiągnięto lepsze bezpieczeństwo pracy systemu i zmniejszenie zakłóceń. (**Analiza stabilności system konwersji energi wiatru o różnej prędkości z wykorzystaniem sterowania bazującego na sieci neuronowej**)*

Keywords: wind energy conversion systems, sensitivity analysis, dynamic feedforward neural network, power output.
Słowa kluczowe: konwersja energii wiatru, sieci neuronowe.

Introduction

In recent years, wind energy industry has developed rapidly, renewable energy provided for people has been gradually increasing by wind energy, installed capacity's growth rate of wind turbines has been increasing more than 25% annually, when the wind speed is above the rated value, the blade pitch angle is controlled to keep the stable output power. The control methods include PID control, nonlinear feedback control (NFC) and linear parameters varying (LPV) gain-scheduling control, PID control limits the wind turbine to run at linear steady-state operating point, once the wind turbine deviates slightly from this position, it will cause the system unstable. The NFC state feedback controller designed for the wind turbine can not guarantee the global asymptotic stability of WECS, and LPV control only ensures $H\infty$ stability of WECS but not the uncertainty caused by the unknown disturbance parameters, WECS have strongly nonlinear at run time, it will be affected by many factors, so the LPV gain-scheduling control is not ideal.

Because of neural network's advantage on dealing with uncertainty of nonlinear system, and not depending upon its mathematical models, it has been applied in many fields, such as flight control, pattern recognition and robot control, etc. Literature [1] studies neural network predictive control in WECS, the results show that using neural network as the predictive controller can improve forecasting accuracy for different wind turbines. Literature [2] designs pitch angle controller using neural network, the results show that the power output is stable during high wind speed, and overloading of the wind turbine was prevented.

The mathematical models of wind wheel, driven system and wind power systems are given in this paper, slow dynamics blade pitch angle was gotten by observer, a new type DFNN compensator is designed based on NNPID to reduce disturbances of the system caused by uncertain parameters, sensitivity analysis method is choosed to optimize structure of the DFNN compensator. Results show that the method can effectively maintain stable power output, a better idea is provided for a smooth integration of wind farm into the utility grids.

Wind energy conversion system

The variable-speed variable-pitch WECS has four work conditions: The variable-speed variable-pitch WECS has four work conditions:

1) $V \prec V_c$, when the wind speed V is below the rated wind speed v_C ,the wind turbine does not work, $P_w = 0$.

2) $V_c \prec V \prec V_r$, when the wind speed is between the cut-in wind speed V_c and rated wind speed V_r ,control target is to capture the largest wind energy, $P_w(t) = C/_R\, v(t)^3 C_P(\lambda)|_{OP}$.

3) $V_r \prec V \prec V_o$, when the wind speed is between the rated wind speed vr and the cut-out wind speed vo, control target is to regulate the output power by the variable pitch-servo system, $P_w(t) = C/_R\, v(t)^3 C_P(\lambda,\beta)|_{OP}$.

4) $V_O \prec V$,when the wind speed is above the cut-out wind speed vo, the wind turbine does not work, $P_w = 0$.

The main structure of the WECS is shown in Fig.1,it can be seen, the WECS are consisted by wind wheel, rigid drive train, double-fed asynchronous wind generator, AC/DC/AC converter and grid.

$$\begin{cases} \Gamma(t) = C v(t)^2 C_\Gamma(\lambda,\beta) \\ \Omega_w(t) = P_w(t)/\Gamma(t) \\ C_\Gamma(\lambda,\beta) = C_p(\lambda,\beta)/\lambda \\ P_w(t) = C/_R\, v(t)^3 C_P(\lambda,\beta) \\ \dot{P}_a = \Gamma_a[J_1\Gamma - J_2\Gamma_a + \dot{\Gamma}_a\Omega_a/\Gamma_a] \end{cases} \tag{1}$$

From Eq.(1), $v(t)$ is wind speed, $\Gamma(t)$ is wind wheel torque, $C = 0.5\pi\rho R^3$, ρ is the air density, R is radius of the wind wheel, $C_\Gamma(\lambda,\beta)$ is torque coefficient, β is blade pitch angle, λ is the tip speed ratio and $\lambda = \Omega_w(t)R/v$, $\Omega_w(t)$ is wind wheel speed, $C_p(\lambda,\beta)$ is power coefficient. $J_1 = 1/J_w$, $J_2 = -i/J_w\eta$, i is the ratio of gear box, η is transmission efficiency, J_w is torque inertia of the wind wheel, J_a is torque inertia of the wind generator. P_a is generator power, $P_w(t)$ is wind wheel power, Γ_a is generator torque, Ω_a is generator speed.

$$\begin{cases} \dot{\Omega}_w(t) = J_1\Gamma(t) + J_2\Gamma_a(t) \\ \dot{\Omega}_a(t) = J_3\Gamma(t) + J_4\Gamma_a(t) \end{cases} \tag{2}$$

where $J_3 = \frac{\eta}{iJ_a}$, $J_4 = \frac{-1}{J_a}$.

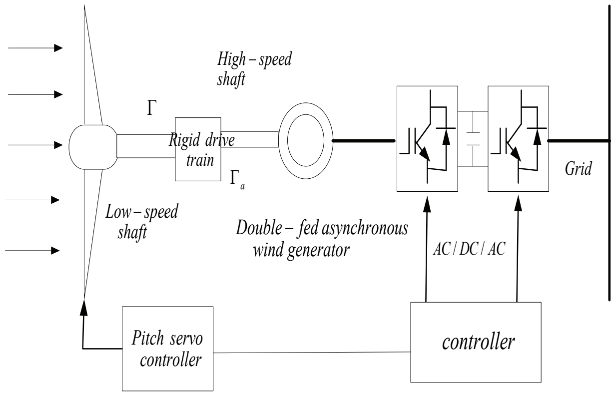


Fig.1. WECS Structure

Definition: based on singular perturbation method [3] ,let's denote slow dynamics wind speed as v_s ,fast dynamics wind speed as Δv ,where $v = v_s + \Delta v$, meanwhile, letting, $\beta = \beta_s + \Delta\beta$, $\Gamma = \Gamma_s + \Delta\Gamma$, where β_s is slow dynamics blade pitch angle, $\Delta\beta$ is fast dynamics blade pitch angle. Γ_s is slow dynamics wind wheel torque, $\Delta\Gamma$ is fast dynamics wind wheel torque.

Transfer function of the variable pitch-servo dynamics system can be expressed by Eq.(3):

(3) $$\frac{\beta(s)}{\beta_r(s)} = e^{-T_\beta s}$$

Where β_r is reference blade pitch angle. T_β is time constant of the variable pitch-servo system. Eq.(4) can be obtained by derivation of the Eq.(1):

(4) $$\begin{aligned}\dot{\Gamma} &= \frac{\partial\Gamma}{\partial\Omega_W}\dot{\Omega}_W + \frac{\partial\Gamma}{\partial\beta}\dot{\beta} + \frac{\partial\Gamma}{\partial v}\dot{v} \\ &= Cv^2\frac{\partial C_T}{\lambda}\frac{R}{v}\dot{\Omega}_W + Cv^2\frac{\partial\Gamma}{\partial\beta}\dot{\beta} + Cv(2C_T - \lambda\frac{\partial C_T}{\partial\lambda})\end{aligned}$$

Letting,

(5) $$\begin{cases} k_1 = CC_T\frac{\lambda}{C_T}\frac{R}{\lambda v}\frac{\partial C_T}{\partial\lambda} \\ k_2 = Cv^2\frac{1}{v}C_T(2 - \frac{\lambda}{C_T}\frac{\partial C_T}{\partial\lambda}) \\ k_3 = Cv^2C_T\frac{\partial C_T}{\partial\beta}\frac{1}{C_T}\frac{1}{\beta_S}\beta_S \end{cases}$$

Parameters vector of the slow dynamic subsystems can be expressed as: $k_{s1}\big|_{\Gamma_S,\Omega_{WS},\lambda_s}$, $k_{s2}\big|_{\Gamma_S,V_S,\lambda_s}$, $k_{s3}\big|_{\Gamma_S,\lambda_s,\beta_s}$. K_S is corresponding slow dynamics parameters matrix. Dual dynamic models of WECS can be expressed as:

(6) $$\dot{P}_{as} = \Gamma_{as}\left[J_1\Gamma_s - J_2\Gamma_{as}\right]$$

(7) $$\Delta\dot{p}_a = \frac{1}{J_W}(\Delta k_1 + k_{1s})\Delta p_a + \frac{\eta}{J_W}\Gamma_s[(\Delta k_2 + k_{2s})\Delta v + (\Delta k_3 + k_{3s})\Delta\beta]$$

As parameters matrix $\Delta K = K - K_S$,Eq.(8) can be obtained by Eq.(4)：

(8) $$\Delta\Gamma = k_1\Delta\Omega_{WS} + k_2\Delta\beta + k_3\Delta v$$

From equation $\beta = \beta_s + \Delta\beta$, Δv and Γ_{as} can be expressed as:

(9) $$\begin{cases} \Delta v = \frac{v_s\Delta\Gamma}{(2-\gamma)} - \frac{\gamma\Delta\Omega_w}{(2-\gamma)\Omega_{ws}} \\ \Gamma_{as} = -\frac{\gamma\Delta P_a\Delta v}{(2-\gamma)\Omega_{ws}} \end{cases}$$

where, $\gamma = \frac{\partial C_T}{\partial\lambda} / \frac{C_T}{\lambda}$, Δv is fast dynamics wind speed, Γ_{as} is slow dynamics wind generator torque.

Analysis of approximation ability of the dynamic feedforward neural network

Hidden layer structure of DFNN can be adjusted in real time by the complexity of the controlled object. Hidden layer structure adjustment of DFNN is: by the analysis of output sensitivity factor, network structure could be streamlined and optimized by deleting unnecessary neurons, this way saves the network training time, it has good adaptability in complex dynamic system, and it has been generally applied in uncertain nonlinear system identification and control [4].

sensitivity analysis of dynamic feedforward neural network

Number of the hidden layer neurons is regulated by analysing the weights's impact on the network output between hidden layer and output layer, numbers of the neuron in the hidden layer is adjusted, then the neural network structure is optimized and the dynamic performance of the neural network is improved [5].

(10) $$\omega_u^{\ 3} = \frac{1}{2}(\omega_{ij}^{\ 3} + \omega_{ij.n}^{\ 3})$$

where $\omega_u^{\ 3}$ is weight of the new neurons inserted in Eq.(10), $\omega_{ij.n}^{\ 3}$ is the neuron's weight whose sensitivity closest to n-th neuron of the hidden layer, sensitivity function is expressed as:

(11) $$S_h = \frac{Var_{\omega_{ij}^3}[E(y/w^3 = \omega_{ij}^{\ 3})]}{Var(y)}$$

where $\omega_{ij}^{\ 3}$ is neuron weight from hidden layer to output layer in Eq.(11), w^3 is the input, *y* is the output, if $w = \omega_{ij}^{\ 3}$, then $E = y$, and $y = F(w^3_1, w^3_2, \cdots w^3_N)$, $Var_{\omega_{ij}^3}$ is the variance of $\omega_{ij}^{\ 3}$, S_h is the contribution amount to the corresponding output.

Normalized error of S_h can be expressed as:

(12) $$S_{sh} = \frac{S_h}{\sum_{n=1}^{N} S_h}$$

Adjustment of the hidden layer neurons based on sensitivity analysis can be divided into three steps:

(I)if $S_{sh} \geq \sigma_1$, where σ_1 is a given positive number, so contribution of the n-th neuron in hidden to output of the network is too large, then the neuron need to be splited.

(II)if $S_{sh} \leq \sigma_2$, where σ_2 is a given positive number,it can be known contribution of the n-th neuron in hidden layer to output of the network is too small, so the neuron need to be removed from the hidden layer,and its associated weights need to be deleted also.

(III)re-training the neural network, the corresponding weights are given by adjusting number of the hidden layer neurons, then the optimized network structure can be obtained, the network is trained by Levenberg-Marquardt (L-M) algorithm.

Data of the wind turbine can be collected by the wind farm SCADA systems,e.g.,rotor speed,pitch angle, power output. The data collected by wind farm SCADA systems is shown in table 1, $v(t)$ is wind speed, $v(t-1)$ is wind speed at previous sampling time period t-1, $x_1(t)$ is wind generator speed, $x_1(t-1)$ is wind generator speed at previous sampling time period t-1, $x_2(t)$ is blade pitch angle, $x_2(t-1)$ is blade pitch angle at previous sampling time period. y in Eq.(13) is output power of wind generator[6],initial numbers of the

$$y = f(v(t), v(t-1), x_1(t), x_1(t-1), x_2(t), x_2(t-1)) \tag{13}$$

neurons N are 2,20and 50 in hidden layer, remaining numbers of the neurons Nr are 15,18 and 20.100 groups of the WECS data is trained to approximate Eq.(13), after 2000 step training, the error is close to 0, the approximation results are shown in table 2, including the average absolute error(MAE), relative mean absolute error(RMAE), standard deviation of MAE(STD1), standard deviation of RMAE (STD2),it can be seen: when N=50 and Nr=20,the approximate effect is ideal.

Table 1. SCADA wind farm data collected

Sample point	v(t)	v(t-1)	···	x1(t)	x1(t-1)
1	9.025	8.561	···	43.218	36.206
2	10.239	9.068	···	46.635	43.218
···	···	···	···	···	···

Table 2. Approximate results

Neuron number	MAE	STD 1	RMAE	STD2
N=02/ N_r=15	15.23	21.93	0.11	0.20
N=20/ N_r=18	10.06	15.68	0.05	0.18
N=50/ N_r=20	8.65	12.33	0.03	0.09

DFNN compensator of WECS

Control structure of the WECS is shown in Fig.2, the observer is 2-4-1 BP network, output of which is slow dynamics blade pitch angle, structure of the NNPID compensator is 4-6-3. The quadratic performance function can be expressed as:

$$J = \frac{1}{2} e(t)^2 \tag{14}$$

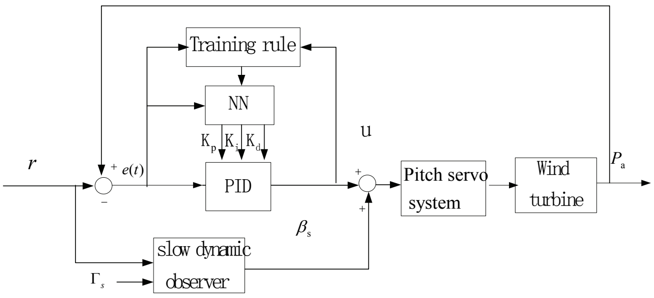


Fig.2. Control structure of wind energy conversion system

Using input and output of the NNPID compensator as the input and output of the DFNN in the paper, weights of the NNPID compensator in hidden layer and output layer are adjusted by the method from literature [7]. Design of the DFNN compensator based on NNPID includes the following steps:

Step1:according to input of the NNPID and output of the NNPID, three-layer DFNN of 4-H-1 structure is selected, *H* is a given natural number,then training the network.

Step2: sensitivity of each neuron output is analysed by Eqs.(11) and (12), calculating its contribution to the output.

Step3: finding maximum output and minimum output of the neurons in hidden layer, removing the contribution value which is less than σ_2, splitting the contribution value which is greater than σ_1, then adjusting the structure of the DFNN.

Step4: using LM algorithm to adjust the network weights

$$W(K+1) = W(K) - ST_n(J^T{}_n I_j + \eta_n I)^{-1} J^T{}_n \zeta_n \tag{15}$$

$J^T{}_n$ is Jacobian matrix of network training error function at the n-step, I is the identity matrix, ζ_n is the n-step error of network training.

Step5: determining whether the desired performance of the system control output is achieved,if not,returning to step 2 re-training the network,if the desired performance is achieved, stopping the training.

Results analysis

The designed DFNN compensator is verified by Matlab simulation,main parameters of the WECS are shown in table 3,6Kw wind generator is token as the controlled object, the second-order reference model is expressed as:

$$G(s) = \frac{w^2{}_n}{s^2 + \zeta w_n s + w^2{}_n} \tag{16}$$

where $w_n = 100$, $\zeta = 0.8$,the overshoot of the reference model is 0.0153,the regulating time is 0.05s. Time constant of pitch servo system T_β is 10s.

Design steps of the DFNN compenstor for the WECS including 5 steps:

Step1: pre-processing input and output data of NNPID compensator, data not met wind power characteristics is filtered out.

Step2:the filtered data must be normalized, desired output is $\bar{x}$,where $\bar{x} = x|_d$, $\Delta x = x - \bar{x}$. normalization error is $\overline{\Delta x}$,where $\overline{\Delta x} = \Delta x / \bar{x}$, range of input and output data of DFNN is [-1,1].

Step3: entering the normalized data into DFNN compensator, adjusting neural network structure.

Step4: normalized errors of generator power, generator torque, and generator speed are restored.

Step5: refering to the expected errors of the systems, revising undesirable output results until the system ouputs achieve satisfactory effect.

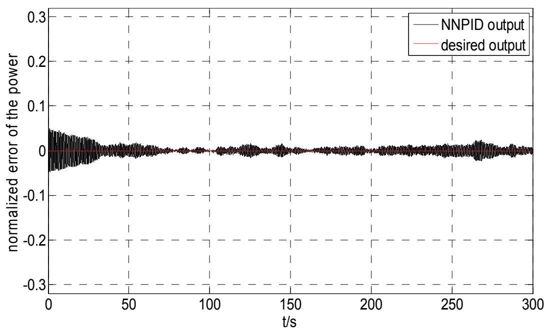
Initial numbers of neurons in hidden layer are 20 and 50, 300 groups data are used to train the DFNN, after 6000-step training,the training error is close to 0,then the numbers of remaining neurons are 17 and 20.

Normalized error outputs of the NNPID control are shown in Figs.3(a)-(c), outputs of the DFNN control are shown in Figs.5(a)-(c), it can be seen from the two figures the two compensators can both keep the output power stable, but the DFNN control effect is better, especially when the wind speed changes rapidly, the DFNN control output power fluctuation is less than NNPID.

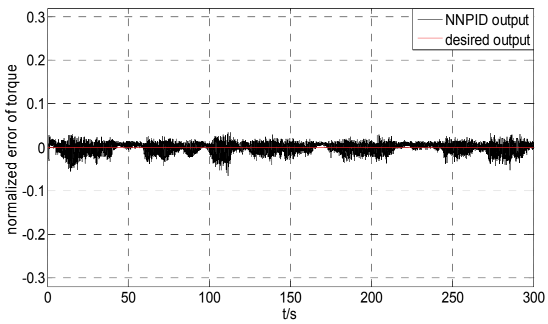
Simuliation models of wind speed are built up by method of literature [8], output of the wind speed is shown in Fig.4. The normalized error outputs of DFNN control with different optimized structure are shown in Figs.5(a)-(c), normalized error of the power with 20 remaining neurons is smaller than that with 17, and the mechanical loading oscillations is less, that is ,the appropriate network structure can reduce the power output's fluctuations caused by disturbance parameters.

Table 3. Parameters value

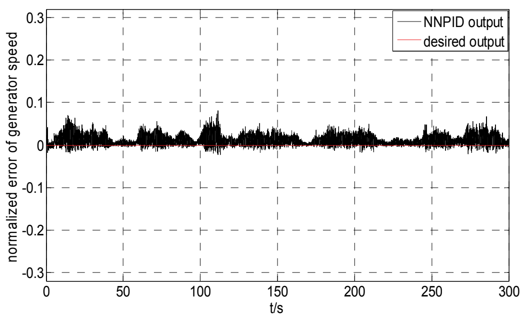
Parameter	value	Parameter	value
R	2.5m	v_o	30m/s
i	6.25	Ω_r	200 rad/s
η	0.95	Γ_r	40Nm
T_β	0.05s	Vr	12m/s
v_c	3.5m/s	P_r	6000w



(a)Normalized error of the power



(b)Normalized error of the generator torque



(c) Normalized error of the generator speed
Fig.3. Output of the NNPID control

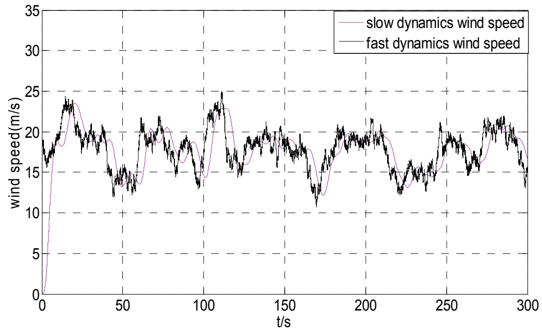
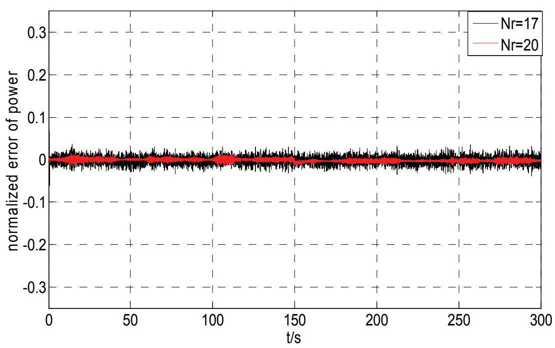
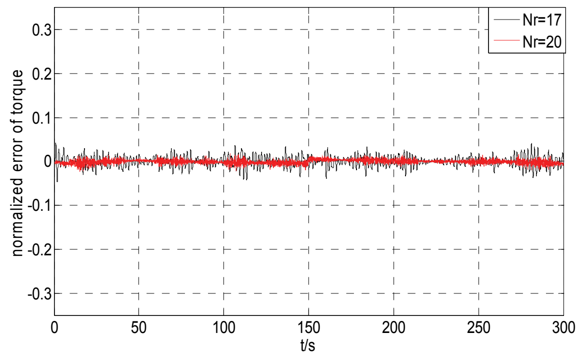


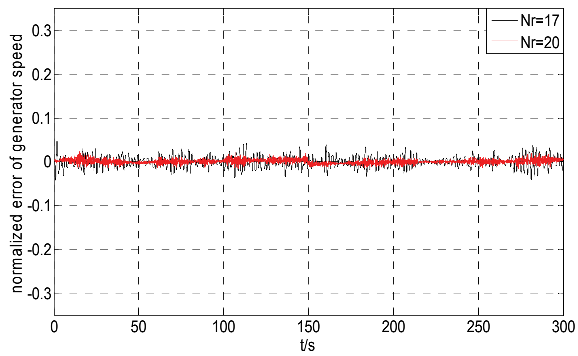
Fig.4. Wind Speed



(a)Normalized error of the power



(b) Normalized error of the wind generator torque



(c) Normalized error of the wind generator speed
Fig.5. Output of the DFNN control

Conclusion

Considering that the wind speed is above rated value,a new type DFNN compensator of the slow dynamics blade pitch angle is designed based on NNPID. Using method of sensitivity analysis to optimize the neural network structure.The control effect is verified by the wind farm SCADA systems data, approximation capabilities of the DFNN is analysed by three groups of average absolute error,relative mean absolute error, standard deviation of MAE,standard deviation of RMAE.

The controls effect of different structures' DFNN are compared and analysed by Matlab simulation,it is confirmed that the system output disturbances caused by unkown parameters can be effectively reduced by the DFNN compensator,this method can maintain stability of the wind turbine power output, safety of the WECS is enhanced,a good idea is provided for the DFNN application in wind power systems field.

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REFERENCES

[1] Kittipong Methaprayoon, Chitra Ying vivatana pong, Wei-Jen Lee, James R. Liao, et al. An Integration of ANN Wind Power Estimation Into Unit Commitment Considering the Forecasting Uncertainty[J].IEEE Transactions on Industray Applications, 43 (2007), No.6:1441-1448.

[2] Ahmet Serdar Yilmaz, Zafer OZer. Pitch Angle Control in Wind Turbines above the Rated Wind Speed by Multi-Layer Perceptron and Radial Basis Function Neural Networks[J]. Expert Systems with Applications, 36 (2009) ,No.6: 9767-9775.

[3] Luis F.C, Alberto. Uniform Approach For Stablility Analysis of Fast Subsystem of Two–Time–Scale Nonlinear Systems [J]. International Journal of Bifurcation and Chaos, 17(2006) No.(11): 4195-4203.

[4] Irmela Zentner,Stefano Tarantola,E.de Rocquigny.Sensitivity Analysis for Reliable Design Verification of Nuclear Turbosets[J].Reliability Engineering & System Safety, 96 (2011) No.3:391-397.

[5] Andrea Saltelli,Marco Ratto,Stefano Tarantola,et al. Sensitivity Analysis Practices: Strategies for Model-Based Inference[J].Reliability Engineering and System Safety,91 (2006), No.(11-12):1109-1125.

[6] Andrew Kusiak,Zijun Zhang,Mingyang Li.Optimization of Wind Turbine Performance With Data-Driven Models[J].IEEE Transactions on Sustainable Energy,1 (2010), No. 2: 66-76.

[7] Pirabakaran,V.M.. Becerra.PID Autotuning Using Neural Networks and Model Reference Adaptive Control[C]. Proceeding of 15th the International Federation of Automatic Control, Spain :Barcelona,15(2002):.

[8] Munteanu I., Barcu A. I., Cutululis N. A.,et al. Optimal control of Wind Energy Systems[M].London:Springer-Verlag, (2008).

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