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. NNPIID 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 energii wiatru o różnej prędkości z wykorzystaniem sterowania bazującego na sieci neuronowej)

Keywords: wind energy conversion systems, sensitivity analysis, dynamic feedforward neural network, power output.

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, non-linear 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 NNPIID 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) $V>V_c$, when the wind speed $V$ is below the rated wind speed $v_c$, the wind turbine does not work, $P_w=0$.
2) $V>V_c>V_r$, 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, $P_w(t)=\frac{1}{2}\rho V^3 r^2 C_p(\lambda, \beta)$
3) $V>V_r>V_o$, when the wind speed is between the rated wind speed $v_r$ and the cut-out wind speed $v_o$, control target is to regulate the output power by the variable pitch-servo system, $P_w(t)=\frac{1}{2}\rho V^3 r^2 C_p(\lambda, \beta)$
4) $V<V_o$, 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.

\[
\begin{align*}
\Gamma(t) &= C_v(t)^3 C_r(\lambda, \beta) \\
\Omega_v(t) &= \frac{P_w(t)}{\Gamma(t)} \\
C_r(\lambda, \beta) &= C_s(\lambda, \beta) \lambda \\
P_w(t) &= \frac{1}{2}\rho V^3 r^2 C_p(\lambda, \beta) \\
\dot{\lambda} &= \Gamma, \dot{\beta} = i \dot{\beta} \\
\end{align*}
\]

From Eq. (1), $\nu(t)$ is wind speed, $\Gamma(t)$ is wind wheel torque, $C = 0.5\pi r^2 \rho \lambda$, $\rho$ is the air density, $R$ is radius of the wind wheel, $C_r(\lambda, \beta)$ is torque coefficient, $\beta$ is blade pitch angle, $\lambda$ is the tip speed ratio and $\lambda = \Omega_v(t) R / \nu$, $\Omega_v(t)$ is wind wheel speed, $C_p(\lambda, \beta)$ is power coefficient. $J_s=1 / J_s$, $J_g=1 / J_g \eta$, $i$ is the ratio of gear box, $\eta$ is transmission efficiency, $J_s$ is torque inertia of the wind wheel, $J_g$ is torque inertia of the wind generator. $P_s$ is generator power, $P_w(t)$ is wind wheel power, $\Gamma_s$ is generator torque, $\Omega_v$ is generator speed.

\[
\begin{align*}
\dot{\Omega_v}(t) &= J_s \Gamma_s(t) + J_s \dot{\Omega_v}(t) \\
\dot{\Omega_v}(t) &= J_g \Gamma_g(t) + J_g \dot{\Omega_v}(t)
\end{align*}
\]
where \( J_s = \frac{\varphi}{\Omega_s} \), \( J_a = \frac{1}{J_s} \).

\[
\Delta p_s = \sqrt{J_s(J_r - J_s)}
\]

\[
\Delta p_c = \sqrt{J_r} \left[ (\Delta \Omega_k + k_v) \Delta \Omega + \frac{\partial \Omega}{\partial \Omega} \Gamma_k (\Delta k_v + k_v) \Delta w + (\Delta k_v + k_v) \Delta w \right]
\]

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

\[
\Delta \Gamma = k_v \Delta \Omega + k_v \Delta \beta + k_v \Delta w
\]

From equation \( \beta = \beta_s + \Delta \beta \), \( \Delta v \) and \( \Gamma_{aw} \) can be expressed as:

\[
\begin{align*}
\Delta v &= \frac{v_k \Delta \Gamma}{2 - \gamma} - \gamma \Delta \Omega_s \left( \frac{2 - \gamma}{1} \right) \\
\Gamma_{aw} &= \gamma \Delta P_c \Delta v \left( \frac{2 - \gamma}{1} \right)
\end{align*}
\]

where, \( \gamma = \frac{\partial \Omega}{\partial \lambda} \), \( \Delta v \) is fast dynamics wind speed, \( \Gamma_{aw} \) 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 analyzing 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].

\[
\omega_{i,j} = \frac{1}{2} (\omega_{i,j} + \omega_{i,j}^*)
\]

where \( \omega_{0,i} \) is weight of the new neurons inserted in Eq.(10), \( \omega_{0,i}^* \) is the neuron's weight whose sensitivity closest to n-th neuron of the hidden layer, sensitivity function is expressed as:

\[
S_{h} = \frac{\text{Var} \omega_{i,j} [E(y/w^3 = \omega_{0,i}^*)]}{\text{Var}(y)}
\]

where \( \omega_{0,i}^* \) is neuron weight from hidden layer to output layer in Eq.(11), \( w^3 \) is the input, \( y \) is the output, if \( w = \omega_{0,i}^* \), then \( E = y \), and \( y = F(w_{1}, w_{2}, \ldots, w_{N}) \), \( \text{Var} \omega_{i,j} \) is the variance of \( \omega_{0,i}^* \), \( S_{h} \) is the contribution amount to the corresponding output.

Normalized error of \( S_{h} \) can be expressed as:

\[
S_{ah} = \frac{S_{h}}{\sum_{i=1}^{N} S_{h}}
\]

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

(i) If \( S_{h} \geq \xi \), where \( \xi \) 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 split.

(ii) If \( S_{h} \leq \xi \), where \( \xi \) 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, \(x_i(t)\) is wind generator speed, \(x_i(t-1)\) is wind generator speed at previous sampling time period t-1, \(x_i(t)\) is blade pitch angle, \(x_i(t-1)\) is blade pitch angle at previous sampling time period, \(y\) in Eq.(13) is output power of wind generator[6],initial numbers of the 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

<table>
<thead>
<tr>
<th>Sample point</th>
<th>(v(t))</th>
<th>(v(t-1))</th>
<th>(x_1(t))</th>
<th>(x_1(t-1))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9.025</td>
<td>8.561</td>
<td>43.218</td>
<td>36.206</td>
</tr>
<tr>
<td>2</td>
<td>10.239</td>
<td>9.068</td>
<td>46.635</td>
<td>43.218</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Table 2. Approximate results

<table>
<thead>
<tr>
<th>Neuron number</th>
<th>MAE</th>
<th>STD 1</th>
<th>RMAE</th>
<th>STD2</th>
</tr>
</thead>
<tbody>
<tr>
<td>N=0/2 N=15</td>
<td>15.23</td>
<td>21.93</td>
<td>0.11</td>
<td>0.20</td>
</tr>
<tr>
<td>N=20/ N=18</td>
<td>10.06</td>
<td>15.68</td>
<td>0.05</td>
<td>0.18</td>
</tr>
<tr>
<td>N=50/ N=20</td>
<td>8.65</td>
<td>12.33</td>
<td>0.03</td>
<td>0.09</td>
</tr>
</tbody>
</table>

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:

\[
J = \frac{1}{2} v(t)^2
\]

Fig2. 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 \(\sigma_2\), splitting the contribution value which is greater than \(\sigma_1\), then adjusting the structure of the DFNN.

Step4: using LM algorithm to adjust the network weights

\[
\sum_{j=1}^{n} w_{kj} y_j(t) + d_k(t) = y(t) = \frac{w_a^T}{s^2 + \zeta_1 s + \zeta_2} \text{where} w_a = 100, \zeta_1 = 0.8, \text{the overshoot of the reference model is 0.0153, the regulating time is 0.05s. Time constant of pitch servo system} T_r \text{is 10s.}
\]

Design steps of the DFNN compensator 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 \(\tau\), where \(\tau = x_1, \Delta_1 = x - \tau\). Normalization error is \(\Delta\), where \(\Delta = \Delta_1/\tau\), 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: referring to the expected errors of the systems, revising undesirable output results until the system outputs 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.

Simulation 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.
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 unknown 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.

ACKNOWLEDGMENTS

This work has been Supported by 111 Project under Grant NO.18 B12018 Intelligent control of industrial processes for innovation & introducing intelligence base Jiangnan University Zhicheng Ji , A Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions, Research Fund for the Doctoral Program of Higher Education of China (Priority Development Areas) under Grant NO.20110093130001.

REFERENCES


Authors: Dr. Li tao, Key Laboratory of Advanced Process Control for Light Industry (Ministry of Education), Jiangnan University, Wuxi, 214122, China, E-mail: teilytl@163.com. Prof. Ji zhicheng, Key Laboratory of Advanced Process Control for Light Industry (Ministry of Education), Jiangnan University, Wuxi, 214122, China, E-mail: zcji@jiangnan.edu.cn.