Research on Control Design on PMSG Based on LSTM

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Abstract. The traditional control method of permanent magnet synchronous generator (PMSG) needs multiple rounds of tuning and test to ensure the dynamic characteristics of the PMSG to reach the standard. It is complex if there are a large number of PMSGs needs to design parameters of the control loops. In order to simplify the tuning and testing process of the control parameters of the PMSG, a data-driven based control method of a PMSG is proposed in this study. It can fit the standard dynamic characteristics by learning the inputs and outputs of the standard dynamic response curves using the long short term memory LSTM method. Subsequently, the proposed control method can be applied to multiple PMSGs, which is convenient and no staff is involved. Finally, a power system connected with a PMSG is as an example. It demonstrates that the dynamic of the PMSG adopted the proposed control method is same with that of the standard PMSG.

1. Introduction
Direct-driven permanent magnet synchronous wind generators have become one of the main development directions of modern speed-variable frequency-constant wind generators due to their advantages of small mechanical loss, high operating efficiency, gear boxes free, low maintenance cost and high reliability [1]. With the increasing capacity of wind generators connected to the power grid, the degree of mutual influence between the power grid and wind generators is also increasing, and in-depth study of the control strategy of direct-driven wind generators grid-connected has important practical significance and value [2].

Random changes in wind speed and direction will cause changes in the wind area of the wind generator blade, thus affecting the power output. Modern control technology requires that when the wind speed changes rapidly, the control system also needs to adjust quickly, and the regulation rate can be kept up with the rate of wind speed change, so that the reliability of unit operation and the stable output of unit power can be effectively ensured. According to the types of controllers, the control strategies of wind generators are mainly divided into the following two categories: traditional PI control methods and modern control methods based on mathematical models.

The conventional PI vector control method has simple structure and clear physical significance, while there are problems such as insufficient power decoupling, poor dynamic response characteristics and strong dependence on the model, which require the PI parameters to be calibrated. Therefore, the risk of system oscillation may occur, which makes it difficult to achieve satisfactory control effect. [3].

How to effectively use the existing fan operation data and knowledge to realize the optimal control of the system under the condition that the controlled system model is unknown or vague is a major problem facing at present. Data-driven control is a form of intelligent control. The controller design does not contain the mathematical model information of the controlled process. It only uses the data of
the controlled system and the knowledge obtained from data processing to design the controller. Under certain assumptions, there are control theories and methods with convergence, stability guarantee and robustness conclusions [4]. In this paper, the pitch angle control in the fan control link was taken as the starting point, and the feasibility of replacing the traditional PI control mode with the data-driven control mode was verified experimentally.

2. Modelling of Pitch Angle Control Strategy for Wind Generator

The total unit dynamic model of wind generator is shown in figure 1:

The mechanical power of a wind generator is mainly determined by the total energy of the wind flowing through the wind generator and the wind energy utilization coefficient of the wind generator itself, which can be expressed as [5]:

\[ P_n = \omega_n T_n = \frac{1}{2} C_r(\lambda, \beta) \rho S \lambda v^3 = \frac{1}{2} C_f(\lambda, \beta) \rho \pi R^2 \lambda v^3 \]  

where \( \omega_n \) and \( T_n \) are the actual output power, angular velocity and torque of the wind generator, respectively.

The following figure shows the block diagram of the principle of pitch angle regulation of wind power generation system based on PI regulator.

It can be seen from figure 2 that the pitch distance signal \( \beta_1 \) is obtained by PI regulation using generator speed feedback, while when the wind speed is higher than the rated wind speed, the pitch angle \( \beta_2 \) is obtained by PI regulation using output power feedback so that it is used as a compensation signal. These two signals are added together to ensure good stability of the control system.
If the neural network method is used for data-driven control to replace the traditional PI regulator, the following control strategy diagram can be obtained.

![Figure 3. Control strategy diagram of pitch angle based on LSTM](image)

The measured input $\omega$, $P$, and measured output $\beta$ of a large number of fan systems in practical operation are given to LSTM for learning and training. If it can output fixed dynamic characteristics in any input, it can play a role as a data drive link instead of PI regulator.

3. Principle of Long- and Short-Term Memory Neural Network

Long- and short-term memory neural networks are temporal recurrent neural networks that learn long-term dependent information, which differ from traditional recurrent neural networks (RNNs) and general neural networks in the way neurons are connected [6-10].

3.1. LSTM Network Structure

The core idea of LSTM is to change the gradient with a number of decimals from a continuous to an additive form, and this method allows LSTM to solve the problem of gradient disappearance when processing long-term timing information [11]. Its structure is shown in figure 4.

![Figure 4. Structural diagram of LSTM neural network](image)

In the figure: $x_{t-1}, x_t, x_{t+1}$ are the network input variables at time $t-1$, $t$, and $t+1$, respectively; $h_{t-1}, h_t, h_{t+1}$ are the short-term states of output at time $t-1$, $t$, and $t+1$, respectively; $c_{t-1}, c_t$ are the
network memory states at time $t-1$ and $t$, respectively; $f_t, i_t, o_t$ are the forgetting gate, input gate, and output gate, respectively; $\sigma$ is the sigmoid activation function; and $g_t$ is the control gate that updates the input state at time $t$. The LSTM Memory Module is shown in figure 5.

When the control gate is in the open state, the control gate is not closed by $i_t, f_t, o_t, g_t$. The transmission information $i_t, f_t, o_t, g_t$ of these four gate units is calculated as $i_t = \sigma(w_{ix}x_t + w_{ih}h_{t-1} + b_i)$, $f_t = \sigma(w_{fx}x_t + w_{fh}h_{t-1} + b_f)$, $o_t = \sigma(w_{ox}x_t + w_{oh}h_{t-1} + b_o)$, $g_t = \tanh(w_{gx}x_t + w_{gh}h_{t-1} + b_g)$, respectively. Where $w_{ix}, w_{ix}, w_{fx}, w_{ox}, w_{ix}, w_{ox}$ is the weight matrix; $b_i, b_f, b_o, b_g$ are the bias terms of $i_t, f_t, o_t, g_t$, respectively. After the information processing of the gate unit, $c_{t-1}$ of the memory conveyor updates its own state and transforms to $c_t$. The update formula for $c_t$ is

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \hat{g}_t$$ \hspace{1cm} (2)

The output $y_t$ of the LSTM module is calculated as

$$y_t = h_t = o_t \cdot \tanh(c_t)$$ \hspace{1cm} (3)

### 3.2. Training Algorithm for LSTM Network

![LSTM training flow diagram](image-url)

The diagram illustrates the training process of the LSTM network, including setting the number of network layers, neurons, initializing weights and biases, setting iteration and learning rate, propagating the network forward, calculating the output of hidden and output layers, calculating the error of hidden and output layers, calculating the partial derivative, updating network weights and biases using backpropagation, and iterating until the maximum number of iterations is reached. The algorithm is verified when the maximum number of iterations is not reached, and the process is ended when the maximum number of iterations is reached.
First, the output value of each LSTM cell is calculated in the forward direction; then the error term of each cell is calculated in the reverse direction, and the gradient of each weight is calculated using the corresponding error term; finally, the weight is updated by the gradient descent algorithm.

The LSTM training flow chart is shown in figure 6. The parameters stored in the traditional PI controller only have a good regulation effect on the input of a specific range, i.e. When the input signal fluctuates exceeded, the previous parameter adjustment may make the adjustment time longer or even the system oscillates all the time difficult to achieve stability. Based on the above problem, neural network was used to calculate the appropriate value of P and I according to the input error, and then the adjusted P and I were sent to the PI controller, so as to dynamically adjust the input. The three parameters of the digital PI controller were no longer present, but were calculated according to the results of the neural network. The above structure could effectively use the effective solution ability of neural network to nonlinear problems and the rapid response ability of PI, so as to accurately and quickly regulate the controlled object.

![Figure 7. Neural network controller structure based on traditional PI regulator](image)

4. Simulation Experiments

![Figure 8. Block diagram of the model of PMSG access to a stand-alone infinite system](image)

MATLAB/Simulink was used to build a PMSG access single-machine infinite system model. The data matrix with generator side speed and output power as input and wind generator pitch angle as output was collected and trained to obtain a data-driven PI controller. The output response comparison, error analysis diagram, error autocorrelation analysis diagram and error histogram of traditional PI control and digital PI control under different system states were analysed by replacing the obtained controller with the PMSG control system. The normal operating conditions are shown in the following figure:
Figure 9. Comparison and error analysis of pitch angle output of traditional and digital PI controller under normal operation of power grid.
View from figure 9, the output response of the digital PI controller under the normal operation condition of the power grid has only a small error of $10^{-3}$ levels in the initial time, i.e. The output response almost perfectly fits the target response generated by the traditional PI controller; the autocorrelation of the error remains at a very low limit ($10^{-11}$), indicating that this digital PI controller predicts the trend that the model should have for complete prediction; the error histogram shows that the error value is very concentrated in a very small interval, and the error analysis experimental results are accurate and credible.

In actual operation, the voltage on the grid side of fan access may change. A voltage short-time drop was set on the grid side through Simulink module, and then whether the data-driven PI controller can still meet the accurate and rapid regulation ability was observed under different operating conditions.

1) When the PMSG operates with a 5% short-time voltage drop in the grid, it can be obtained

(a) Comparison and error of output response

(b) Autocorrelation of errors
2) When the PMSG operates with a 17% short-time voltage drop, it can be obtained that

(c) Error histogram

Figure 10. Comparison and error analysis of pitch angle output of traditional and digital PI controllers under 5% short-time voltage drop in power grid
Through figure 10 and figure 11, it can be seen that even if there is a short-time voltage drop, the output response of the digital PI controller can still accurately fit the traditional PI controller, the error is still very small, the autocorrelation of the error is still very low, and the error value is still concentrated in a very small interval, indicating that this digital controller can maintain stable dynamic characteristics with the change of the system parameters provided by the network side in the single-machine infinite system.

5. Conclusion

According to the system characteristics and variable pitch control of wind generator, a data-driven controller based on LSTM is designed to replace the traditional PI controller. The simulation experiment shows that this method can produce accurate nonlinear control action without relying on accurate mathematical model. The output of PI controller obtained by neural network through the training results of a large number of data is well fitted to the output of traditional PI controller and has good dynamic characteristics. It also eliminates the problem that the traditional PI controller needs to set the parameters separately in the face of the differentiated system, which can provide the wind generator system with fixed dynamic characteristics under different inputs and facilitate the stable operation of the wind generator system.
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References
[1] Dan, W. Research on control strategy of grid-connected converter system for direct-driven wind generator, North China Electric Power University (Beijing), 2016, pp 1-26.
[2] Jian, C., Haifeng, W.: 'Model-data hybrid driven VSC equivalent modeling method for direct-drivers', Power System Protection and Control, 2021, 49 (02), pp 10-17.
[3] Zengping, W., Guosheng, Y., Yong, T., et al.: 'Wind electric field modeling of direct-driven on feature impact factor and improved BP algorithm', Chinese Journal of Electrical Engineering, 2019, 39 (09), pp 2604-2615.
[4] Qiang, W., Qi, J., Gangui, Y.: 'Analysis of sub-synchronous oscillation characteristics of weak AC wind driven field', Renewable Energy, 2019, 37 (08), pp 1171-1178.
[5] Chen, W., Peng, K.: 'Multi-fan wind speed prediction in wind farms based on convolutional neural network and simple cycle unit integration model', Journal of Electrical Technology, 2020, 35 (13), pp 2723-2735.
[6] Q. Fu, W. Du, and H. F. Wang, et al., “Small-Signal Stability Analysis of a VSC-MTDC System for Investigating DC Voltage Oscillation,” IEEE Trans. Power Syst., early access, 2021.
[7] Zhiyan, Z., Zhaoyu, Z., Tingshu, Y., et al.: 'Fault diagnosis of permanent magnet synchronous generator based on fuzzy neural network', Micromotor, 2019, 52 (11), pp 27-30.
[8] Linfu, W., Danfeng, X., Hushan, Z., et al.: 'Research on modeling and simulation method of direct-driven permanent magnet wind generation system', Electronic Measurement Technology, 2019, 42 (20), pp 44-50.
[9] Bin, L., Guanghui, L., Jiajun, W., et al.: 'Modeling of machine side DC impedance of permanent magnet synchronous wind generator', Electrical Drive, 2020, 50 (06), pp 109-114.
[10] Lili Y.: 'Analysis of mechanism and characteristics of sub-synchronous oscillation of wind generator system', Guangxi University, 2020, pp l-40.
[11] Zhenkui, W., Xinyu, M., Lei, X., et al.: 'Maximum power tracking of permanent magnet direct-drive wind power system', Automated Applications, 2019 (06), pp: 110-113.