Short-circuit Current-based Parametrically Identification for Doubly Fed Induction Generator

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Abstract. Recently, deep learning has provided a new opportunity to achieve high precision and real-time parameter identification of the doubly-fed induction generator (DFIG) in the event of short-circuit fault. However, deep learning algorithms based on data training are facing the challenge of relying on a large amount of training data and poor generalization performance. In order to improve these shortcomings, we embed the forward calculation model of three-phase short-circuit current (SCC) into the neural network, and propose an unsupervised neural network which can realize high-precision parameter identification. The network only needs to convert the short circuit current curve into a two-dimensional gray level map to complete the precise training of the network without real labels, which effectively improves the fitting ability of the network for inverse problems. The simulation results show that the proposed method can achieve high precision identification of DFIG parameters both within and outside the domain, and verify the high precision identification and generalization ability of unsupervised networks.

Keywords: DFIG; SCC; Parametrically Identification; unsupervised network; Deep Learning.

1. Introduction

Wind energy has recently gained special attention, which is an important renewable energy with commercial application prospects. Doubly fed induction generator-based wind turbines (DFIG-WTs) are widely used in wind power generation system because of its advantages, such as high utilization rate, small inverter capacity and power decoupling control. When a short-circuit fault occurs in a power system, a large short-circuit current (SCC) will be contributed by DFIG-WTs in the wind farm [1]. The security and stability of power system will be greatly affected by SCC. An accurate calculation of SCC is of great importance for relay protection setting and optimization design of electrical equipment [2]. The SCC contribution of DFIG is dictated by a combination of factors, including the electrical parameters of the machine and the controller configuration of the converters [3].

An accurate calculation of SCC depends on establishing a reasonable dynamic equivalent model for wind farm. Wind farm modeling methods based on DFIG have been widely concerned [4],[5],[6],[7]. Accurate SCC calculation and control of wind turbines depend on accurate model parameters of wind turbines. Effective identification of turbine parameters is of great significance for improving the performance of wind turbines [8][9][10].

With widely application of deep learning, deep learning provides an opportunity for DFIG parameter identification for DFIG. However, deep learning algorithms based on data training are facing the challenge of relying on a large amount of training data and poor generalization performance. In order to improve these shortcomings, we embed the forward calculation model of three-phase short-circuit current into the neural network, and propose an unsupervised neural network which can realize high-precision parameter identification. The rest of this article is organized as follows. Section II describes the mathematical model of DFIG; Section III illustrates the parameters identification method based on unsupervised learning; Section III gives experimental results to verify the proposed methodology; and Section IV gives the conclusion.

2. Mathematical Model of DFIG

Motor convention is applied on the relevant electrical parameters of the stator and rotor sides of DFIG. The magnetic saturation effect of the magnetic circuit of the generator is neglected. The electromagnetic transient model [1] of DFIG in the synchronous reference frame are given by:

$$\begin{cases} u_s = R_s i_s + \dfrac{\mathrm{d}\psi_s}{\mathrm{d}t} + j\omega_s \psi_s \\ u_r = R_r i_r + \dfrac{\mathrm{d}\psi_r}{\mathrm{d}t} + j\omega_p \psi_r \end{cases} \tag{1}$$

and

$$\begin{cases} \psi_s = L_s i_s + L_m i_r \\ \psi_r = L_m i_s + L_r i_r \end{cases} \tag{2}$$

where $u_s, u_r, i_s, i_r, \psi_s, \psi_r, R_s, R_r, L_s, L_r$ are the voltage, current, flux, resistance and inductance of the stator and the rotor windings, respectively. $L_s = L_{s\sigma} - L_m$ and $L_r = L_{r\sigma} - L_m$, $L_{s\sigma}$ and $L_{r\sigma}$ are the stator and rotor leakage inductance, respectively. L_m is the magnetizing inductance. $\omega_p = \omega_s - \omega_r$ is the slip angular velocity, where ω_s and ω_r are the synchronous angular speed and rotor speed respectively.

According to (2), the stator and rotor currents can be expressed as

$$\begin{cases} i_s = \dfrac{\psi_s}{L_s'} - k_r \dfrac{\psi_r}{L_s'} \\ i_r = -k_s \dfrac{\psi_s}{L_s'} + \dfrac{\psi_r}{L_r'} \end{cases} \tag{3}$$

$$\begin{cases} L_s' = L_s - \dfrac{L_m^2}{L_r} = L_{s\sigma} + \dfrac{L_{r\sigma} L_m}{L_{r\sigma} + L_m} \\ L_r' = L_r - \dfrac{L_m^2}{L_s} = L_{r\sigma} + \dfrac{L_{s\sigma} L_m}{L_{s\sigma} + L_m} \end{cases} \tag{4}$$

where L_s' and L_r' represent the transient inductances of the stator and the rotor windings, respectively. $k_s = L_m / L_s$ and $k_r = L_m / L_r$ denote the inductance coefficients of the stator and the rotor.

When three-phase short-circuit occurs in DFIG system, the short-circuit current includes power frequency component, DC component and rotor frequency component. The voltage drop coefficient k_d of stator side is introduced, which is defined as: $k_d = (U_{s0} - U_{s1})/U_{s0}$; U_{s0} and U_{s1} present the voltage of the stator side in space vector before and after the fault occurs, respectively. Then, the voltage of stator side after short-circuit occurs can also be expressed as $U_{s1} = (1-k_d)U_{s0}$.

According to the principle of Crowbar resistance protection, the analytical expression of stator's three-phase short-circuit current in synchronous rotating coordinate system is obtained as follows:

$$i_s = \frac{(1-k_d)U_{s0}}{j\omega_s L_s^{'}} e^{j\omega_s t} + \frac{k_d U_{s0}}{j\omega_s L_s^{'}} e^{-t/\tau_s} - \frac{1}{j\omega_s L_s^{'}} \cdot [U_{s0} - (R_{CB} + j\omega_s L_s^{'}) i_{s0}] e^{j\omega_s t} e^{-t/\tau_r^{'}} \tag{5}$$

where $\tau_s = L_s' / R_s$ represents the stator transient time constant. Based on the discernability of parameters analyzed in [11], five parameters including R_s 、 R_r 、 $L_{s\sigma}$ 、 $L_{r\sigma}$ 、 L_m to be identified were determined. Based on the analysis of three-phase short-circuit current calculation model of DFIG above, the relationship between the SCC of DFIG and these five parameters can be expressed as follows:

$$i_s = H\left(R_s, R_r, L_{s\sigma}, L_{r\sigma}, L_m\right) \tag{6}$$

The equation above establishes a forward physical model between DFIG parameters and short-circuit current.

3. DFIG Parameter Identification Method Based on Unsupervised Learning

3.1 Data Preprocessing

This paper introduces a preprocessing technology that converts one-dimensional signal data into two-dimensional gray image [12]. Since the gray value of each pixel of a 2-D gray image is distributed within an integer value of 0~255. It is assumed that the origin 1-D signal contains N discrete points, and the conversion relationship is as follows:

$$p(i) = round\left\{\frac{l(i) - l_{\min}(i)}{l_{\max}(i) - l_{\min}(i)} \times 255\right\} \tag{7}$$

where $round(\cdot)$ represents the integer operation. According to the input requirements of CNN network, the image size is usually 16*16, 32*32, 64*64, 128*128, etc., so it is necessary to intercept the length of the converted signal value as a vector $1 \times N^2$, and finally convert it into a two-dimensional matrix through matrix transformation. That is, the grayscale image matrix can be expressed as formula (8).

$$\begin{bmatrix} p(i) & \cdots & p(i+N-1) \\ & \vdots & \\ p(i+N^2-N) & \cdots & p(i+N^2-1) \end{bmatrix} \tag{8}$$

The signal conversion process is shown in Fig. 1.

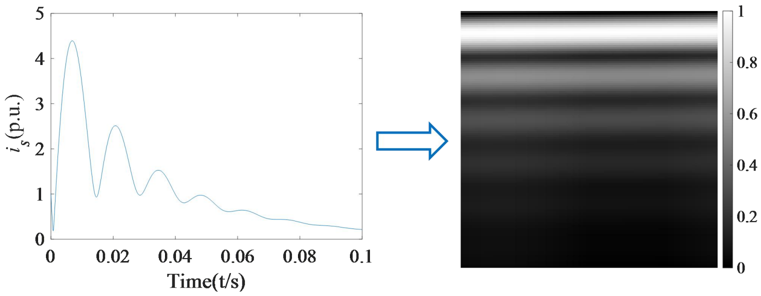

Fig. 1 Conversion of 1-D SCC waveform to 2-D gray level

3.2 Design of Unsupervised Network

The forward physical model described in section II establishes the correspondence between the parameters to be identified and the SCC curve. The purpose of this paper is to identify 5 parameters of DFIG from the SCC curve, which is obviously an inverse problem.

$$[R_s, R_r, L_{s\sigma}, L_{r\sigma}, L_m] = H^{-1}(i_s) \tag{9}$$

The traditional data-driven based deep learning identification method uses a large number of labeled paired data to form a training set, and then allows the neural network to fit these data. However, the identification accuracy of this traditional method base DL is very dependent on a large number of labeled training data. To solve this problem, we propose an unsupervised parameter identification method. As shown in Fig. 2, By embedding the short-circuit current calculation model into the network to adjust its parameters, the parameter identification results can be output without data sets:

$$R_{\theta^*} = \arg\min_{\theta} \left\| I - H\left(R_\theta(I)\right) \right\|^2 \quad s.t.[R_s, R_r, L_{s\sigma}, L_{r\sigma}, L_m] = R_{\theta^*}(I) \tag{10}$$

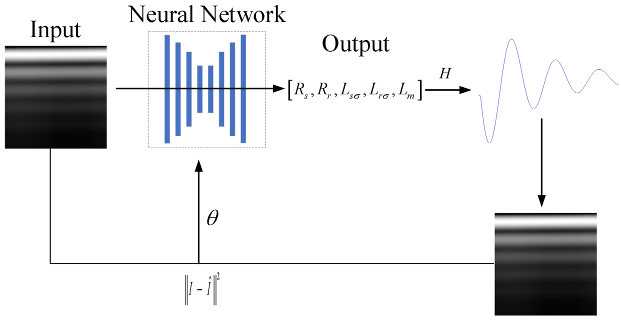

Fig. 2 Principle diagram of DFIG parameter identification for unsupervised learning

It is not difficult to find that the proposed parameter identification method is actually a full combination of model-based optimization algorithm and data-driven-based deep learning. The combination of learning and optimization forms a new paradigm of parameter identification, which not only retains the high performance of optimization algorithm, but also fully solves the generalization problem of DL.

Calculate the cross entropy error between the input and the gray level of the short-circuit current data corresponding to the identification parameters:

$$L\left(I,\hat{I}\right)=-\frac{1}{n}\sum_{k=1}^{n}\left[I_k \ln \hat{I}_k+\left(1-I_k\right)\ln\left(1-\hat{I}_k\right)\right] \tag{11}$$

Equation (11) is taken as the loss function of the neural network, and the Adam optimization algorithm with a learning rate of 0.001 is used for network training. The proposed network architecture is shown in Fig. 3. The network input is a preprocessed two-dimensional gray level of short-circuit current, and the network consists of two convolution layers, two pooling layers and two fully connected layers. Its output is 5 parameter values to be identified. Behind both convolution layers are connected Batch Normalization (BN) and ReLU activation functions, which form a (Conv-BN-ReLU) CBR base unit. Written using the PyTorch 1.13.1 framework, python version 3.7.16, and deployed on a PC with an NVIDIA GeForce GTX 1650 GPU with 4GB RAM.

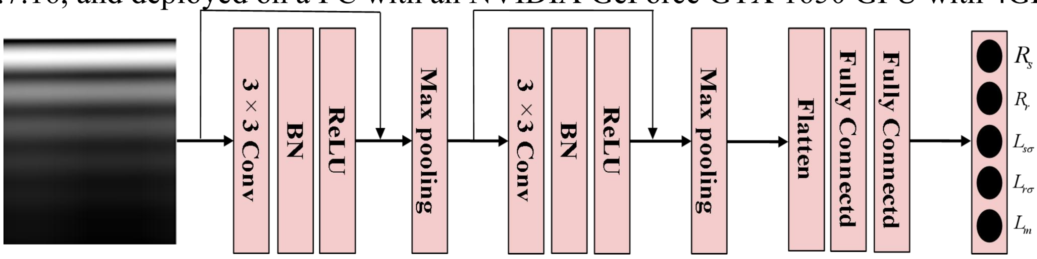

Fig. 3 Network architecture of parameters identification of DFIG

4. Experiments and Results

In order to verify the accuracy of the proposed unsupervised network in parameters identification of DFIG, Simulink-based platform was used to model a 1.5MW wind turbine equipped with Crowbar resistance, and its parameters are shown in Table 1. It is assumed that the wind speed is unchanged before and after the short-circuit fault, which are both 11 m/s, and the slip rate is − 0.18. When $t<0$, the DFIG wind turbine is in steady state, at time $t=0$, the short-circuit fault occurs, and the Crowbar resistor is started immediately for protection, and finally it returns to normal at the moment $t=0.1$, that is, the fault duration is 0.1 seconds.

Table 1. DFIG parameters used in simulation

Parameters	Value	Parameters	Value
R_s/pu	0.023	R_r/pu	0.016
$L_{s\sigma}$/pu	0.18	$L_{r\sigma}$/pu	0.16

L_m/pu	2.9	R_{CB}/pu	2Rr

The unsupervised parameter identification method proposed in this paper is compared with traditional methods, such as particle swarm optimization (PSO), adaptive variant Particle swarm optimization (AMPSO)[11], end-to-end deep learning method (CNN1). The parameter settings of PSO and AMPSO are consistent. As for the end-to-end deep learning method CNN (w/o physics model), the simulation software Simulink was used to randomly generate 4000 pieces of data to form a simulation data set. Parameter identification results are shown in Table II. As can be seen from Table II, the error of parameter identification based on data-driven Deep Learning is obviously much smaller than that based on optimization algorithm, which is a beneficial result of training with large amounts of data. However, the identification error of data-driven DL(CNN1) is still greater than that of improved PSO (AMPSO), which may be due to the strong dependence of data-driven CNN on data and its generalization ability is limited. The unsupervised parameter identification method proposed in this paper is to embed the short-circuit current calculation model in the original CNN training process. The identification accuracy has been effectively improved, and the average identification error has been reduced from 2.98% to 2.20%. Even for the parameters R_s and R_T that are difficult to identify, whose errors have been reduced from 4.78% and 5.81% to 3.48% and 4.37%, respectively. It fully shows that the neural network embedded physical model can correct the wrong results of the network to a certain extent. Fig. 4 shows the short-circuit current curves corresponding to four different identification methods. It can be seen that the overall error of the method proposed in this paper is much smaller than that of other comparison algorithms, which verifies the correctness of the method proposed in this paper.

Table 2. Comparison of parameter identification results

Algorithms	Parameter	R_s	R_r	$L_{s\sigma}$	$L_{r\sigma}$	L_m
PSO	Value	0.0211	0.0168	0.1815	0.1807	2.7898
	Error	8.26%	5.00%	0.83%	12.94%	6.01%
AMPSO	Value	0.0241	0.0151	0.1809	0.1567	2.8503
	Error	4.78%	5.81%	0.51%	2.09%	1.71%
CNN1	Value	0.0240	0.0149	0.1807	0.1636	2.8611
	Error	4.35%	6.88%	0.39%	2.25%	1.34%
CNN2	Value	0.0222	0.0167	0.1806	0.1629	2.8714
	Error	3.48%	4.37%	0.33%	1.81%	0.99%

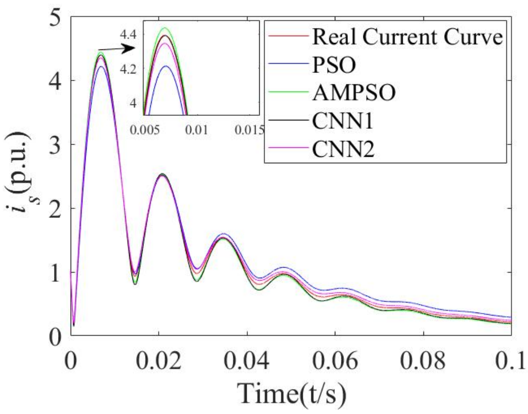

Fig. 4 Current curve of three-phase short-circuit fault identified by four methods

5. Conclusions

The accurate calculation of SCC depends on the accurate identification of DFIG parameters. With deep learning being widely used, deep learning has provided a new opportunity to achieve high precision and real-time parameter identification of the doubly-fed induction generator. This paper investigated an unsupervised neural network for parameter identification of the doubly-fed induction generator based on short-circuit current, which embeds the forward calculation model of three-phase short-circuit current into the neural network, and only needs to convert the short circuit current curve into a two-dimensional gray scale data into network without real labels. We discussed the three-phase short-circuit current calculation model of DFIG and the parameter identification method of DFIG based on unsupervised principle. The simulation results show that the proposed method can achieve high precision identification of DFIG parameters both within and outside the domain, and verify the high precision identification and generalization ability of unsupervised networks.

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