Neural Network Model of Wind Farm Based on DFIGs

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Abstract. Due to the complexity of wind farms for power flow calculation in power system, it is difficult to accurately describe equivalent models in accordance with traditional methods such as weighted average parameters. However, the merit of neural network (NN) is able to mimic nonlinear and complicated function with multiple inputs and multiple outputs (MIMO). The back-propagation (BP) NN is adopted to substitute the wind farm based on doubly-fed induction generators (DFIG) in this paper. To do this, a simple BP model is established to be equivalent to single DFIG. The training data of the NN is obtained by simulation of actual DFIG, in which the wind speed, voltages of DFIGs, optimal power captured strategy are used as inputs and the active and reactive power are as outputs. Furthermore, a multilayer BP model is built and trained to mimic the wind farm based on DFIGs using simulation results of the actual 34 DFIGs, 102 MW electrical network with statistical wind speed and rotor-side voltage. The simulation results show that the BP NN can be used to model the wind farm, simplify the power flow calculation in the power system and be of high accuracy.

1. Introduction

With the development and popularization of wind power technology, more and more large-scale wind farms have emerged in recent decades, which have significant impacts on the power grid. Therefore, it is necessary to establish an efficacious wind farm model.

However, wind farm has a high degree of complexity. If each wind turbine is built as an independent model, it will lead to an excessive calculation cost, which is inconvenient to researchers and is not applicable to grid power flow analysis yet [1]. Therefore, it is very meaningful to establish a simple and accurate wind farm model in the simulation of wind power system.

At present, the equivalent methods can be roughly classified into two categories. One is based on fuzzy logic. This method ignores the internal structure and electrical relationship of the wind farm, and combines the measured data with the neural network (NN) to mimic a wind farm. For examples, the reference [2] uses BP NN method and takes wind speed as its input, the active and reactive power (P and Q) as its outputs. It has certain reference significance, but cannot characterize the differences of wind turbines and its accuracy is not very high; the reference [3] uses the measured rotor phase voltages as additional inputs. It got a good result, but the data selection lacked of some key parameters. The other is based on electrical relationships. Mei and Wan in [4] proposes an equivalent single-machine model for wind farm, which adopts many improvements but it still has large error due to the problems such as uneven wind speed distribution [5] and wake effects [6]. On this basis, some authors propose grouping equivalence. According to different clustering algorithms and various parameter indicators, wind turbines in the wind farm is clustered into several groups, and the equivalent single machine models are performed respectively. Ultimately, a multi-machine model of the wind farm is obtained, which can effectively reduce the complexity of the wind farm. For instance, the wind speed...
in [7], the historical wind data in [8], the data of calculating 13 turbine parameters in [9], and dynamic current error in [10] are used. Although the accuracy of the wind farm model is improved after grouping, the large number of clusters will increase the complexity of the algorithm. The small number of clusters will lose the meaning of clustering. Meanwhile, it deviates from the original intention of taking the wind farm as a node in power system simulation.

The authors intend to establish an equivalent NN model by using the good nonlinear fitting feature of NN. Taken the difference between DFIG and permanent magnet synchronous generator (PMSG) into consideration, this paper mainly focuses on a DFIG NN model based on a real wind farm. The input parameters are selected to follow the electrical relationship, in addition to some statistical parameters which can characterize the differences between the different DFIGs so that it can obtain similar characteristics without being clustered.

2. Single DFIG wind turbine model

The DFIG is very common in wind power generation. The wind turbine’s structure is shown in figure 1. It includes three blades, multi-stage gearbox, generator and back-to-back (BTB) power converter which lies between the rotor side of DFIG and the grid side of the power system. Due to its strong stability at variable wind speed and lower cost, DFIG is widely used in wind power generation. The single DFIG wind turbine model is based on 3MW DFIG in this paper.

![Figure 1. The structure of a DFIG system](image)

![Figure 2. The equivalent circuit of a DFIG](image)

2.1. Single DFIG circuit model

As it is known to all, the DFIG can be described by an equivalent circuit shown in figure 2. Through this circuit, the power expression can be formulated by circuit parameters and terminal voltages as well as the slip.

The appearance power which the DFIG generates can be calculated according to voltage and current phasors at the stator and the rotor terminals. In order to simplify the calculation, the reference directions are shown in Figure 2. Thus, one has:

\[
\dot{S} = mU_r \dot{I}_r^* - mU_s \dot{I}_s^* \quad (1)
\]

where \( \dot{S} \) is the complex power, \( m \) is the phase number, \( U_r \) and \( U_s \) are the rotor and stator voltage phasor respectively, \( \dot{I}_r \) and \( \dot{I}_s \) are the rotor and stator current phasor respectively. The voltages can be expressed as below:

\[
\begin{align*}
U_r &= \dot{I}_r \left[ R_r + j \left( X_r + X_m \right) \right] - \dot{I}_s j X_m \\
U_s &= \dot{I}_s j X_m - \dot{I}_r \left[ R_s + j \left( X_r + X_m \right) \right]
\end{align*}
\]

(2)

(3)

where \( R_m \) is neglected due to relatively small compared to magnetizing reactance \( R_m \ll X_m, R_r, R_s, X_r, X_s \) and \( X_m \) are the rotor, stator resistance, leakage reactance and magnetizing reactance. \( s \) is the slip which is formulated as:

\[
s = \frac{n_0 - n}{n_0} \quad (4)
\]

where \( n_0 \) is the synchronous rotating speed and \( n \) is the rotor rotating speed.
According to the above formulas, the output powers of a DFIG can be determined by quantities \( n \), \( U_r \) and \( U_s \). In order to eliminate the vector parameters, these formulas can be transferred into the forms:

\[
P = \text{Re}[\hat{S}] \quad \dot{U}_r = U_r \angle 0
\]

\[
Q = \text{Im}[\hat{S}] \quad \dot{U}_s = U_s \angle \theta
\]

Therefore, according to single DFIG circuit model, the active power \( P \) and reactive power \( Q \) of the DFIG can be determined by quantities \( n \), \( \dot{U}_r \), \( \dot{U}_s \) and \( \theta \).

2.2. Single DFIG NN model

NN is a widely used method to mimic nonlinear and complicated systems in various fields. An NN is composed of multiple neurons. A neuron can be described as a multiple input and one output nonlinear model. The structure of a neuron model is shown in figure 3.

The output of this neuron model can be described as the following formula for BP and radial basis function RBF respectively:

\[
\text{BP}: y_k = f(b_k + \sum_{i} w_{ik} x_i) \quad \text{RBF}: y_k = f(\|w-x\|b)
\]

where \( x_i \) is the input; \( w_{ik} \) is the weight between \( x_i \) and the neuron \( -k \); \( b_k \) is the bias; \( f(\cdot) \) is the activation function which characterizes the nonlinearity.

![Figure 3. The structure of a neuron-k model](image)

![Figure 4. The 4-input 2-output single DFIG NN model](image)

Since the outputs of the circuit model do not directly affect the input, the forward NN model is selected, as shown in Figure 4.

The BP NN and radial basis function (RBF) NN are two widely used forward NN. The difference between them is the activation function, as the BP usually uses Sigmoid function while the RBF uses Gaussian function.

The following part is aimed to compare these two models and figure out a more suitable NN model for the whole wind farm model.

The number of hidden layer neurons can be determined by the following empirical formulas:

\[
n_i = \sqrt{n + m + a}, \quad n_i = \log_2 n
\]

where, \( n \), \( m \) and \( n_i \) are the number of the input, output and hidden layer neurons respectively; \( a \) is a constant between 1 and 10. According to the 4-input 2-output structure and these formulas, the number of hidden layer neurons is chosen to be 10.
The learning data of NN are obtained from the equivalent circuit model, from which 4000 sets of data are generated. These data are generated from different speed \( n \) (from 811 to 1210rpm, step length is 1rpm, each step has 10 sets) and the values \( U, \theta \) are obtained under optimal tip speed ratio operation. These 4000 sets are used for training the NN and the 1000 randomly generated sets are used for verification of the NN.

2.3. Results and Analysis
This section will compare three kinds of models including 1-3-2 BP NN, 4-10-2 BP NN and 4-X-2 RBF NN.

During training the RBF, in order to decrease the mean square error (MSE) defined in equation (8), it will generate huge amounts of neurons. If the goal of MSE is set to be 0.01, it will produce up to more than 1000 neurons, while its accuracy is close to 4-10-2 BP NN. Meanwhile, if the number of neurons is reduced to less than 20, its outputs have a larger deviation. The reason requiring the great number of neurons is that the active power has a strong correlation with the rotor speed but it has a weak correlation with the other parameters. In order to eliminate the difference, the RBF NN has to add more neurons.

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (T_i - R_i)^2
\]  

where, \( n \) is the number of sets. \( T_i \) and \( R_i \) are the \( i \) th set of test data and the real data respectively.

The absolute errors of models, namely 1-3-2 BP NN, 4-10-2 BP NN, 4-17-2 RBF NN, and 4-1230-2 RBF NN, are shown in figure 5 and figure 6.

Table 1. The Performance of P and Q of P and Q for 4 models

| NN Model       | The Number of Neurons | Max Absolute Error of P (MW) | Mean Square Error of P(%) | Max Absolute Error of Q (MVar) | Mean Square Error of Q(%) |
|----------------|-----------------------|------------------------------|---------------------------|-------------------------------|---------------------------|
| 1-3-2 BP NN    | 3                     | 0.0568                       | 0.0181                    | 1.5491                        | 29.8542                   |
| 4-10-2 BP NN   | 10                    | 0.0385                       | 0.0047                    | 0.0933                        | 0.0286                    |
| 4-17-2 RBF NN  | 17                    | 1.3596                       | 3.1017                    | 1.2549                        | 3.8104                    |
| 4-1230-2 RBF NN| 1230                  | 0.0460                       | 0.0050                    | 0.0899                        | 0.0297                    |
From figure 5, figure 6 and table1, these models demonstrate quite well performance of mimicking the active power except for model3 (4-17-2 RBF NN). The reason is that the learning data are so huge while the number of neurons is too small to find enough cluster centers. With the number of neurons growing in RBF method, the mimicking accuracy can be improved significantly. Both model4 (4-1230-2 RBF NN) and model2 (4-10-2 BP NN) possess the nearly prefer performance.

Meanwhile, model1 (1-3-2 BP NN) cannot mimic the reactive power well, because there are no strong correlation between the reactive power Q and the rotor speed n. Model3 still has poor performance of mimicking the reactive power, but it is better than model1 for adding input parameters which influence the reactive power Q. Both model2 and model4 can mimic the DFIG model well, but too many neurons will pay expensive calculation cost.

As a result, model2 is chosen for further wind farm model research because of both accuracy and simplification.

3. DFIG wind farm model
Since the single DFIG NN model can mimic a DFIG accurately, the wind farm can also be mimicked by NN through changing some input parameters.

3.1. Wind farm power flow model

![Figure 7](image)

In order to obtain the data of wind farm in various situations, a wind farm power flow model is built based on the measured data from an offshore wind farm. Its structure is shown in figure 7.

This wind farm power flow model consists of 34 DFIGs. Each DFIG including its step-up transformer is equivalent to resistance and reactance form. The cable parameters including resistance, inductance and capacitance are determined by the cable's datasheet and measurement data. Each DFIG is considered to be a PQ node, where the active power P is mainly determined by the rotor speed or the wind speed due to the optimal tip-speed ratio control strategy and the reactive power Q can be adjusted between capacitive and inductive power factor 0.9. The PCC node (110/35) is considered to be a reference node so that the total PQ data can get from this node through power flow calculation method. Thus, the whole model owns 69 nodes, including 34 PQ nodes, 34 connection nodes and 1 reference node. Power flow calculation is executed under Matlab environment by using the power flow calculation tool.

Above all, the learning data can be generated by the given wind speed of each DFIGs under statistical law.
3.2. Wind farm NN model

In order to get different situation, a based wind speed is given to the whole wind farm. Each DFIG’s wind speed is determined by the based wind speed and fluctuations in accordance with statistical laws. Each DFIG’s rotor speed can be calculated by its wind speed due to the optimal tip-speed ratio control strategy. Then, one DFIG’s data can be determined by the method in section 2.2. After getting the PQ values of each DFIG, the wind farm power flow model can be used to generate the total PQ values of the wind farm. These two values are the outputs of the wind farm NN model.

The input data are determined by comparing different combinations. According to the result in section 2.2, the wind speed, the stator and the rotor voltages and their phase difference are chosen to be the input data. In order to characterize the differences among DFIGs, the standard deviation of the wind speed, the rotor voltage and the phase difference between the stator and the rotor voltage phasor are also considered to be the input data, which are calculated according to the following formulas.

\[
v_{eq} = \frac{1}{n} \sum_{i=1}^{n} v_i, \quad U_{eq} = U_1 \tag{9}
\]

\[
U_{eq} = \frac{1}{n} \sum_{i=1}^{n} U_{r_i}, \quad \theta_{eq} = \frac{1}{n} \sum_{i=1}^{n} \theta_i \tag{10}
\]

\[
Dv_{eq} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (v_i - v_{eq})^2} \tag{11}
\]

\[
DU_{eq} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (U_{r_i} - U_{eq})^2} \tag{12}
\]

\[
D\theta_{eq} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\theta_i - \theta_{eq})^2} \tag{13}
\]

According to the above method, there are 4000 sets of data generated as the learning data and 1000 sets randomly generated and used for verification of the neural network.

Four BP NN models are established to study the impacts between different inputs and outputs, namely 1-3-2 BP NN, 2-6-2 BP NN, 5-12-2 BP NN and 7-16-2 BP NN.

The differences of their input quantities are as follows:

1) \(v_{eq}\)  
3) \(v_{eq}, Dv_{eq}, U_{eq}, U_{req} \) and \(\theta_{eq}\)  
2) \(v_{eq}\) and \(Dv_{eq}\)  
4) \(v_{eq}, Dv_{eq}, U_{eq}, U_{req}, DU_{eq}, \theta_{eq}\) and \(D\theta_{eq}\)

3.3. Results and Analysis

The relative error of active power is used to compare the accuracy of different models, which is defined as follows:

\[
e_{op} = \frac{P_{out} - P_{real}}{P_{real}} \times 100\% \tag{14}
\]

where \(P_{out}\) and \(P_{real}\) are the active power outputs of the NN and power flow model respectively.

However, the reactive power may be close to zero. If the same method is used as the performance, the relative error may be a great number, which is trivial in confirming the validity. Thus, a comparison error is introduced to be the performance as follows:
\[ e_q = \frac{Q_{\text{out}} - Q_{\text{real}}}{|Q_{\text{real}}| + \sum Q_{\text{real}}} \times 100\% \]  

(15)

where \(Q_{\text{out}}\) and \(Q_{\text{real}}\) are the reactive power outputs of the NN and power flow model respectively. \(\sum Q_{\text{real}}\) is the sum of \(Q_{\text{real}}\) totally 1000 verification data.

Figure 8. The Active Power Relative Error of 4 models

Figure 9. The Reactive Power Comparison Error of 4 models

| Table 2. The Performance of P and Q for 4 models |
|-------------------------------------------------|
| NN Model | The Number of Neurons | Max Relative Error of P(%) | Mean Square Error of REP(%) | Max Comparison Error of Q(%) | Mean Square Error of CEQ(%) |
|----------|------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| 1-3-2 BP NN | 3 | 13.3871 | 2.0952 | 0.5471 | 0.1295 |
| 2-6-2 BP NN | 6 | 10.7332 | 1.8530 | 0.5492 | 0.1293 |
| 5-12-2 BP NN | 12 | 10.0524 | 1.5907 | 0.4528 | 0.1008 |
| 7-16-2 BP NN | 16 | 4.1941 | 0.7089 | 0.3711 | 0.0634 |

Comparing (a)–(d) in figure 8, the accuracy of active power increases apparently due to the increasing neuron number of the input and the hidden layer. Comparing the Max REP (Relative Error of P) and Mean Square Error of REP in Table 2, the P performance of these four models are steadily improved, especially for the model 4. The reason is that adding two input neurons whose inputs characterize the difference between DFIGs will significantly improve the accuracy. Comparing model 1 and model 2, adding one characterization difference input improves the performance significantly. However, comparing model 2 and model 3, adding three inputs which characterize the whole wind farm does not have such a huge change. Thus, it can be found that adding some inputs which characterize the differences has strong correlation in improving the accuracy of mimicking active power.

Meanwhile, the data points in figure 8 (d) mostly lie within 1% error range. Examining those data which have large deviation, it can be found that they occur in lower wind speed status, and the total active power is less than 20MW. It has 4.2% relative error, but it does not cause very large deviation in absolute error.

Comparing (a)–(d) in figure 9, the accuracy of the reactive power also increases and data points are densely close to zero. Conversely, comparing the Max CEQ (Comparison Error of Q) and Mean
Square Error of CEQ in Table2, model1 and model2 have almost the same performance because the wind speed and its standard deviation has weak correlation to the reactive power Q. With adding more related inputs such as rotor voltage information and their deviations, the accuracy can be improved significantly. The model including all seven inputs can make the accuracy better. Thus, adding more related inputs can improve the accuracy of mimicking reactive power because of their strong correlation.

It can be concluded that it is not accurate enough by only using the relationship between wind speed and PQ output value. It is necessary to add other parameters which affect the output to the input parameters in mimicking a wind farm. The introduction of the standard deviation can improve the accuracy of the model.

4. Conclusion

This paper presents BP NN to simplify the complexity of wind farm and guarantees accuracy within acceptable limits. Different NN models of single DFIG are built and BP NN is chosen to mimic a wind farm through measurement data, equivalent circuit model and power flow model of wind farm. In order to find the appropriate inputs parameters, an equivalent circuit model is built in order to obtain active power and reactive power based on the wind speed, stator voltage, rotor voltage and their phase difference. Then single DFIG NN models are established to figure out the NN model which is suitable for building a wind farm model. Due to the large number and high dispersion of learning data, BP NN is more suitable in this situation. Finally, four wind farm NN models which possess one to seven different inputs are established to study the impacts between different inputs and outputs, find the model with better performance to mimic the wind farm. The simulation results show that adding some parameters which can characterize the difference between DFIGs and strong correlation to active and reactive power will significantly improve the accuracy as the model4 in section3 demonstrates the better performance.

It is worth to mention that this BP NN model is suitable for the wind farm DFIGs which run in MPPT state. Since the rotor voltage can be given, combining an appropriate power control strategy and power distribution method can make the whole wind farm to be an adjustable PQ node in power system analysis. In addition, this BP NN model can accurately mimic the steady state characteristics of the wind farm. For the dynamic characteristics and the wind power forecast, more effort should be made in the future.

5. References

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